AL/HR-TR-1993-0091

AD-A270 971

IDENTIFICATION OF EFFECTIVE TEACHING BEHAVIORS

A R M S T R O N G

Patricia Y. Hsieh
Todd M. Miller
Kimberly A. Hicks
Karle P. Lorenz

Mei Technology Corporation
8930 Fourwinds Drive, Suite 450
San Antonio, TX 78239

L A B O R A T O R Y

HUMAN RESOURCES DIRECTORATE
TECHNICAL TRAINING RESEARCH DIVISION
7909 Lindbergh Drive
Brooks Air Force Base, TX 78235-5352

July 1993

Final Technical Report for Period February 1992 - March 1993

Approved for public release; distribution is unlimited.

AIR FORCE MATERIEL COMMAND
BROOKS AIR FORCE BASE, TEXAS

NOTICES

This report has been reviewed and is approved for publication.

KURT W. STEUCK
Contract Monitor

JAMES W. PARLETT, Major, USAF
Chief, Intelligent Training Branch

RODGER D. BALLENTINE, Colonel, USAF
Chief, Technical Training Research Division

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	July 1993	Final February 1992 - March 1993

4. TITLE AND SUBTITLE
Identification of Effective Teaching Behaviors

5. FUNDING NUMBERS
C - F33615-91-D-0651
PE - 61101F
PR - ILIR
TA - 20
WU - 19

6. AUTHOR(S)
Patricia Y. Hsieh
Karie P. Lorenz
Todd M. Miller
Kimberly A. Hicks

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Mei Technology Corporation
8930 Fourwinds Drive, Suite 450
San Antonio, TX 78239

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Armstrong Laboratory (AFMC)
Human Resources Directorate
Technical Training Research Division
7909 Lindbergh Drive
Brooks Air Force Base, TX 78235-5352

10. SPONSORING/MONITORING AGENCY REPORT NUMBER
AL/HR-TR-1993-0091

11. SUPPLEMENTARY NOTES
Armstrong Laboratory Technical Monitor: Dr. Kurt Steuck, (210) 536-2034

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*
The purpose of this study was to identify effective human teaching behaviors and ways of implementing them in an intelligent tutoring system (ITS). This information was then used to develop a set of production rules to demonstrate how this instructional approach could be implemented in a computer-based format. This study found that much of the existing educational research literature is applicable to intelligent tutoring system development. However, translating effective teaching research into specific rules that can be executed by a computer was not easy.

14. SUBJECT TERMS
Education
Training
Intelligent computer-aided instruction
Intelligent tutoring systems

15. NUMBER OF PAGES
174

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form 298 (Rev 2-89)
Prescribed by ANSI Std Z39-18
298-102

TABLE OF CONTENTS

TABLE OF CONTENTS (CONT.)

LIST OF FIGURES

LIST OF TABLES

PREFACE

This report describes findings from a study to identify effective human teaching behaviors and ways of implementing them in intelligent tutoring systems. It is hoped that this type of research will both integrate the education research literature into intelligent tutoring systems development, and serve as a springboard for further research on effective teaching.

The study was undertaken on behalf of the Armstrong Laboratory, Human Resources Directorate (AL/HRTI). Dr. Kurt Steuck was the Air Force task monitor. The authors would like to thank Dr. Steuck for initiating the investigation, for the use of his personal library, and for his invaluable guidance throughout the effort.

SUMMARY

The purpose of this study was to identify effective human teaching behaviors and ways of implementing them in an intelligent tutoring system (ITS). This information was then used to develop a set of production rules to demonstrate how this instructional approach could be implemented in a computer-based format. It is hoped that this sample rule set can eventually be used to help develop an effective teaching *template* for use in a variety of intelligent tutoring systems in the future.

The study consisted of four major tasks. Table 1 describes these tasks and their respective inputs and outputs.

Table 1. Summary of Project Tasks.

TASK	INPUT(S)	OUTPUT(S)
1. Review of the literature on effective teaching behaviors (Chapter 2)	Research literature on various aspects of effective teaching (e.g., presentation techniques, motivation, questioning, feedback)	Identification of effective teaching behaviors
2. Review of instructional approaches (Chapter 3)	Research literature on selected instructional approaches (direct instruction, discovery learning, mastery learning, cognitive apprenticeship)	Decision to use cognitive apprenticeship approach as a framework for incorporating effective teaching behaviors
3. Review of formats for knowledge representation on the computer (Chapter 4)	Literature on techniques for knowledge representation (e.g., production rules, semantic nets, predicate logic) and organization (e.g., blackboard, list of rules)	Decision to use a list of production rules as a format for representing effective teaching knowledge
4. Demonstrate how effective teaching knowledge can be implemented in a computer-based knowledge representation format (Chapter 5 and Appendixes A, B, and C)	Outputs from Tasks 1-3	1) An outline of instructional decisions involved in implementing the cognitive apprenticeship approach; 2) a set of instructional variables; and 3) rules which demonstrate how the cognitive apprenticeship approach could be implemented on a computer

This study found that much of the existing educational research literature is applicable to intelligent tutoring systems development. However, translating effective teaching research into specific rules that can be executed by a computer was not easy, for a number of reasons. The major ones were: 1) there is so much information about effective teaching that it was not possible to review all the relevant areas; 2) the literature is often unclear as to exactly how to implement teaching behaviors; 3) the literature is particularly unclear on the issue of how to individualize instruction (which is usually a major reason for using a tutor in the first place); and 4) computers are more limited than human teachers in their ability to handle multiple goals simultaneously; and to continuously monitor the teaching situation.

Recommended areas for future research include: 1) operationalize and test the sample rule set on an intelligent tutoring system; 2) review other relevant areas of the literature (e.g., screen design, media selection, effective use of visuals); 3) more research on how to individualize instruction (e.g., studies which examine how various aptitudes, traits, and treatments interact); and 4) continue to track technology developments which would make it possible to use more powerful and versatile methods of representing knowledge on the computer.

IDENTIFICATION OF EFFECTIVE TEACHING BEHAVIORS FOR INTELLIGENT TUTORING SYSTEMS

I. INTRODUCTION

Intelligent tutoring systems (ITSs) are computer-based systems which--in theory--utilize artificial intelligence (AI) techniques to provide highly individualized instruction, much like that of a human tutor. The attempt to utilize AI in computer-assisted instruction (CAI) has been going on for more than twenty years, dating back to Carbonell's seminal article, *AI in CAI: An Artificial Intelligence Approach to Computer-Assisted Instruction* (1970). However, programming a computer to do the things that human teachers do has proven to be a very difficult task.

One of the major problems in intelligent tutoring system development has been identifying what effective human teachers do. At least four different approaches have been taken to the development of the tutoring component of ITSs:

- *Inspired programmer*. Tutoring principles are derived primarily from the developers' instincts about what constitutes good tutoring. This often happens when tutoring is not the main focus of the effort. For example, ITS researchers are sometimes particularly concerned with some aspect of ITS programming, such as techniques for detecting student errors, or fitting an ITS over an existing expert system (Brown and Burton's *BUGGY*, 1978; Clancey's *GUIDON*, 1984). Although this approach can produce acceptable instruction, it is not optimal.

- *Theory driven*. Tutoring principles are based on some type of theory. Usually this is either cognitive theory (e.g., Anderson, Boyle, and Reiser's Lisp and Geometry tutors, 1985) or theory derived from computer-assisted instruction (e.g., Tennyson and Park's *MAIS*, 1987). If the theory is well-established, this can be an effective approach. Another advantage is that it gives developers a basis for using particular teaching strategies. However, a disadvantage is that most cognitive or educational theories are not comprehensive enough to generate all possible effective teaching strategies. Furthermore, evolution of the theory necessitates significant changes in the teaching strategies used.

- *Human tutor modeling*. This approach involves closely observing human tutors' actions and making inferences about their reasoning, followed by construction of a computer model which mimics their actions (Collins, Warnock, & Passafiume's *WHY*, 1975). This approach can offer a high degree of validity *if* there is a great deal of similarity between the role and knowledge of the human tutor and the expected role and knowledge of the ITS. Validity will be compromised if the human tutor is not experienced, or if the human tutor only provides help with homework assignments, but the ITS is expected to teach the course.

Even if similarity is high, a potential disadvantage of the expert tutor modeling approach is that an ITS which merely mimics human expert tutors may fail to utilize fully the media strengths of the computer, such as its animation, gaming, and simulation capabilities.

- *Integrative*. This approach involves deriving tutoring principles from the available research literature on effective teaching behaviors (e.g., O'Neil, Slawson, & Baker, 1991). Effective teaching behaviors are here defined as anything a teacher does that helps a student to learn what the teacher intends the student to learn. These may include techniques for motivating the student, explaining a concept more clearly, or encouraging the student to learn independently. Even activities which are not directly related to presenting subject matter, such as teaching study skills, may be considered to be effective teaching behaviors if they enable students to learn more effectively.

  This approach offers a certain degree of convenience, in that all developers have to do is read studies and distill principles. They do not have to set up a study or develop a theory--although they do need to be discriminating about the studies they choose. In addition, it allows developers to pick and choose well-grounded instructional principles for implementation within the ITS.

  There are several problems associated with the integrative approach, however. The body of educational research is incomplete and often inconclusive. In addition, much of the existing research has been conducted in classroom or laboratory situations, and therefore some findings may not be as effective when transferred to a one-on-one computer-based instructional environment. Finally, developers must figure out effective ways of *combining* teaching behaviors whose effectiveness was likely established in *isolation*. For example, both advance organizers and visual organizers (such as concept maps) have been found to be effective in some situations. But if used together for instruction, should they be presented separately or combined (e.g., using a concept mapping exercise as an advance organizer)?

Each approach has advantages and disadvantages. Both the type of approach selected and the quality of its implementation can influence the instructional effectiveness of the ITS. This report describes a study by Armstrong Laboratory (AL/HRTI) which used the integrative approach. Although this approach has some potential problems as discussed earlier, it was selected because: 1) the arguments against it do not appear to be very strong (Goodyear, 1991); and 2) this approach has never been attempted in a comprehensive manner.

The goal of this study was to produce domain-independent research-based

guidance for the development of the tutoring component of ITSs. This guidance will ultimately be made available to intelligent tutoring systems researchers, developers, and programmers in some readily computer-digestible form. It is hoped that this will allow ITS development time to be shortened and educational effectiveness to rise.

The following major tasks were undertaken in support of this research effort:

- Review and assessment of the literature on effective teaching behaviors for applicability to implementation within intelligent tutoring systems
- Review of instructional approaches and selection of one (cognitive apprenticeship) to be used as a framework for implementing effective teaching behaviors
- Review of computer-based knowledge representation formats and selection of one (list of production rules) for representing effective teaching knowledge
- Integration of all the above into 1) an outline of cognitive apprenticeship decision processes, 2) a list of instructional variables; and 3) a sample set of production rules.

The objectives, activities, and products associated with these steps will be described in greater detail in the following chapters.

II. REVIEW OF THE LITERATURE

Broadly speaking, effective teaching behaviors can be defined as anything a teacher does that helps a student to learn what the teacher intends the student to learn. These may include techniques for motivating the student, explaining a concept more clearly, or encouraging the student to learn independently. Even activities such as counseling may be considered to be effective teaching behaviors, if they enable students to learn more effectively. Consequently, there is a vast amount of literature that pertains to effective teaching behaviors.

However, not all effective teaching behaviors are applicable to intelligent tutoring systems. For example, empathizing with students' struggles or counseling students on their personal problems is best left to human teachers (at least for the present). Conversely, there are some things a computer can do--such as provide animation, simulation, and arcade-type games--which the average human teacher would be hard-put to provide. Since the purpose of this task was to identify effective teaching behaviors for ITS implementation, the criteria in Table : were used to prioritize topics in the literature for review.

Table 2. Criteria for Prioritizing Topics for Literature Review.

PRIORITY	EASE OF IMPLEMENTATION	USEFULNESS	EXAMPLE TOPICS
high	easy	broad	Providing feedback
medium	easy	restricted	Use of simulation
low	difficult	broad	Cooperative learning
non-select	difficult	limited or questionable	Personal counseling

Over 300 journal articles and books in the following areas were reviewed:

- Elements of instructional presentation - e.g., advance organizers, concept maps, modeling, explaining, coaching, scaffolding, simulation

- Motivation - e.g., assessment of motivation, computers and motivation, tutoring and motivation, attribution, locus of control, self-efficacy

- Areas for student assessment (both before and during instruction) - e.g., educational history, academic motivation, general motivation, cognitive style, learning style

- Questioning techniques - e.g., question types, levels of questioning, sequencing

- Feedback - e.g., timing, content, response certitude, interaction with student characteristics

- Learning strategies - e.g., metacognition, comprehension monitoring, rehearsal, elaboration, organizational strategies

The more relevant articles and book chapters were summarized and evaluated, and *teaching rules* were derived based on the conclusions whenever possible. The purpose of developing teaching rules was to express knowledge about effective teaching in the form of instructions. These instructions could then be easily converted later to a form for computers. In deriving the rules, the researchers tried to be as specific as possible about what to do and when to do it, because unlike humans, computers need to be told exactly what to do when. For example, the following three rules were derived from an article on feedback (cf., Schultz, 1992):

- If response certitude is high and the response is correct, little feedback is required.

- If response certitude is high and the response is incorrect, provide informational feedback.

- If response certitude is low, provide informational feedback.

In practice, however, it was usually difficult to obtain a high level of specificity, because the literature itself was not very specific. Often rules took the following form: *To increase intrinsic motivation, allow student to make choices.* This type of rule is less helpful, because it does not give much specific information about when to allow choice. After all, it is *always* desirable to increase intrinsic motivation.

The following sections summarize the literature reviewed, and the implications for intelligent tutoring systems development. These sections include:

- Elements of instructional presentation
- Motivation
- Areas for assessment
- Questioning strategies
- Feedback
- Learning strategies

Elements Of Instructional Presentation

Elements of presentation are like *instructional tools*. They are designed to help teachers and students reach specific learning objectives. This section addresses some of the more commonly-used elements of presentation. For each element, there will be a definition, a statement of purpose, a summary and evaluation of relevant research, and recommendations regarding its applicability to intelligent tutoring systems. The following elements will be discussed:

- Advance organizers
- Visual organizers
- Mnemonics
- Learner control
- Scaffolding and fading
- Modeling and telling

Advance Organizers

Definition

An advance organizer is a presentational technique that attempts to encapsulate what a learner already knows in light of upcoming instruction. Supposedly, this technique facilitates learning and retention by providing the learner with explicit connections between existing knowledge and novel material (Ausubel, 1977). Generally, advance organizers are text-based passages, although graphic and aural organizers are also common (Luiten, Ames, & Ackerson, 1980). Advance organizers, according to Ausubel, have the following characteristics:

- They are presented prior to instruction.
- They focus on the ties between already learned and novel material.
- They are abstract, general, and inclusive statements of fact.

Assimilation theory is often invoked to describe the effects of advance organizers (Ausubel, 1977). Theoretically, an advance organizer prompts the learner to transfer key information from long-term to short-term memory. Once in short-term memory, this information is activated. Activated knowledge anchors new knowledge by subsuming it under broad, pre-existing categories. In this way, cognitive structure is fleshed out. We can see that abstract, general, and inclusive statements are better anchors, according to assimilation theory, because they prompt the learner to draw upon broader and therefore more subsuming sources of knowledge. The organizer acts as a bridge between what the learner already knows and the instructional content. Advance organizers, then, tailor new knowledge to existing cognitive structure (Ausubel, 1977; Krahan & Blancher, 1986).

Purpose

Ausubel (1977) has most succinctly defined the purpose of the advance organizer. According to him,

> *...the principal function of the organizer is to bridge the gap between what the learner already knows and what he needs to know before he can successfully learn the task at hand.*

In short, advance organizers are employed to facilitate meaningful learning and promote retention of novel material by causing an active integration of new and old information (Krahan & Blancher, 1986).

Summary and Evaluation of the Research

Generally, advance organizer research focuses on: 1) learner characteristics, 2) conditions of learning, and 3) organizer characteristics.

<u>Learner Characteristics</u>

It is likely that certain learner characteristics (e.g., age) moderate the effectiveness of advance organizers. Possibly, advance organizers work for some types of learners but not others. If this is indeed the case, then the design and use of advance organizers must be carefully considered. The effects of *grade level*, *subject ability*, and *subject knowledge* are examined. Recommendations are presented at the end of the section.

Grade level. Stone (1983), using meta-analysis, found mean effect sizes for preschool (1.01), elementary (.64), junior high (1.39), high school (.45), and college

students (.49). Luiten, Ames, & Ackerson (1980) found smaller effect sizes favoring the use of advance organizers for learning and retention criteria across grade level. Mean effect sizes ranged from .17-.33 indicating that the average individual receiving an advance organizer performed better than approximately 57-63% of control subjects. These results suggest two things. First, advance organizers seem to improve performance across grade level. Second, younger populations tend to benefit most from advance organizers. The second finding is problematic, however. Large standard errors were associated with these effect sizes. This means that if we were to construct confidence intervals around these estimates of effect size, the intervals would be quite large and they would overlap. Therefore, it is difficult to say with any conviction that grade level moderates the effectiveness of advance organizers. We can reasonably conclude that advance organizers facilitate learning across grade level. Despite the obvious variability in the reported effect sizes across grade, certain methodological factors (e.g., number of studies, sizes of the standard errors) make conclusions about specific grades risky.

Subject ability. Luiten et al. (1980) examined the effectiveness of advance organizers for three subject ability groups: high (.23), medium (.08), and low (.13). In similar work, Stone found mean effect sizes for high (.34), medium (.64), and low (.26) ability students. Again, standard errors in both studies were large enough to prohibit conclusive interpretations. The only conclusion that we can reach is that, generally, advance organizers promote learning and retention across ability levels.

Subject knowledge. Subject knowledge is similar to ability except that it is domain-specific. Stone reports mean effect sizes for high (.24), medium (.27), and low (.032) knowledge students. Simply looking at these figures suggests that advance organizers are more effective for non-novice students although the number of studies in each category averages only 5. Interpretation of results based on a study sample size of 5 is problematic. Unfortunately, it is difficult to say anything about the relationship between subject knowledge and the effectiveness of advance organizers.

Conditions of Learning

Conditions of learning refer to characteristics of the learning environment which are defined by the curriculum or teacher.

Subject area. Luiten et al. (1980) examined the effectiveness of advance organizers for learning and retention criteria in mathematics, and the physical, biological, and social sciences. The results are shown in Table 3. Once again, study sample size and error confound interpretation. For example, a 95% confidence interval for retention criteria in mathematics would provide the following interval: $(-.048 < ES < .248)$. The lower limit is negative. With an observed effect size of .17, it is possible that advance organizers may actually *hinder* retention in mathematics. However, it is reasonable to conclude that *in general*, advance organizers slightly facilitate both learning and retention across subject areas.

Table 3. Mean Effect Sizes of Advance Organizers by Domain and Criterion.

CRITERIA FOR ASSESSING EFFECTIVENESS	MATHEMATICS	PHYSICAL SCIENCES	BIOLOGICAL SCIENCES	SOCIAL SCIENCES
LEARNING	.10	.15	.11	.13
RETENTION	.17	.50	.18	.26

Organizer C aracteristics

Characteristics of the organizers themselves may moderate effectiveness. Characteristics examined include: mode of presentation, type, style, hierarchy type, source, and operational level.

Mode of presentation. Luiten et al. (1980) compared written and aural advance organizers in terms of effectiveness. Both had a facilitative effect on learning. Written advance organizers had a facilitative effect of .17, while aural advance organizers had a facilitative effect of .37. This effect size difference of .20 translates to a 7.7% improvement in average performance over control when aural organizers are used in place of written organizers. It is not always possible or even desirable to use aural organizers, however.

Type. Kloster & Winne (1989) compared the effects of different types of advance organizers on learning from text. Concept, analogy, outline, and dummy organizers were employed. They found no main effects by organizer type although the effectiveness of an organizer was related to the student's ability to relate new information to the organizer. They concluded that the *true* advance organizers like *concept* and *analogy* organizers resulted in superior performance only when students used them efficiently. Often, however, the students had a hard time connecting the information from the lesson to the organizer. This suggests that Ausubel's claim that organizers should be general is not necessarily true.

Style. Expository and comparative advance organizers seem to promote learning better than mixed or narrative organizers. Stone found effect sizes of .80 (expository), .88 (comparative), .18 (mixed), and .29 (narrative). These results suggest two things. First, organizers should adhere to a single style. Second, explanatory and comparative organizers are superior to narrative ones.

Hierarchy type. Hierarchy type refers to whether or not the advance organizer *subsumes* the instructional content (Stone, 1983). That is, does the organizer provide the learner with information which is more abstract and general than the instructional content? Assimilation theory would predict that subsuming information would greatly enhance the effectiveness of the organizer. Stone, on the other hand, found that non-subsuming organizers were slightly better.

Source. Organizer content can be derived from several sources including

previously covered material or future instructional content. Source refers to whether or not the content of the organizer was drawn directly from the instructional material or whether it was designed to bridge old and new knowledge. Stone's results suggest that organizers drawn directly from the instructional content are slightly more effective (Stone, 1983). Again, this finding contradicts assimilation theory. According to the theory, information which bridges old and new knowledge should be more effective. This result suggests that organizers should be drawn directly from the instructional material.

Operational level. Operational level refers to whether the organizer is concrete or abstract. Ausubel claims that abstract organizers are more effective because they activate subsuming concepts. Stone's results contradict Ausubel's position (Stone, 1983). She found that concrete organizers facilitated learning more than abstract ones. This finding suggests that organizers should focus on the specific and concrete features of the knowledge to be learned.

All in all, advance organizers seem to facilitate learning and retention across a variety of circumstances. Unfortunately, the methodological characteristics of many advance organizer studies prohibit full interpretation of the data. Nonetheless, the following general conclusions emerge:

- Advance organizers facilitate learning and retention for most learners.
- Advance organizers facilitate learning and retention across most disciplines.
- Concrete and non-subsuming organizers seem to promote learning better than abstract and subsuming organizers.
- Expository and comparative organizers seem to be better than narrative organizers.
- The use of true organizers (i.e., concept and analogy organizers) should be reserved for use with higher ability students.
- Oftentimes, it desirable to use lesson content as the source for organizer material.

Applicability to Intelligent Tutoring Systems

Advance organizers, including graphic and aural forms, are applicable to intelligent tutoring systems. Unfortunately, the resolution of the research is poor; therefore, we cannot individualize organizers to fit many learner characteristics. Additional research and cumulative studies are necessary to clarify the relationships between organizers, the learner, and achievement.

Concept Maps and Other Visual Organizers

Definitions

Supposedly, visual organizers are graphic representations of innate thought processes (Clarke, 1991). As such, they are metacognitive tools; they help students to recognize and control intellectual processes which bring meaning to lesson content and promote higher-order thinking skills. There are two general classes of visual organizers: *bottom-up* and *top-down*. Bottom-up organizers are inductively-based. That is, they help students to organize information so that they can draw inferences about trends, related concepts, group characteristics, and theories. Clarke (1991) identifies the following examples of bottom-up visuals:

- *Time lines*: Events are plotted along a continuum in chronological order. Time lines allow students to observe trends and identify cause-and-effect relationships.

- *Web diagrams*: A main idea is placed in the hub or center of the web. Related concepts and facts are placed around the perimeter of the hub. For example, the hub of Figure 1 might represent the domain *mathematics* while the perimeter sites might represent *algebra, geometry, statistics* and so forth. Each of the perimeter sites could be further sub-divided. Web diagrams allow students to examine the relationships between ideas, concepts, and facts.

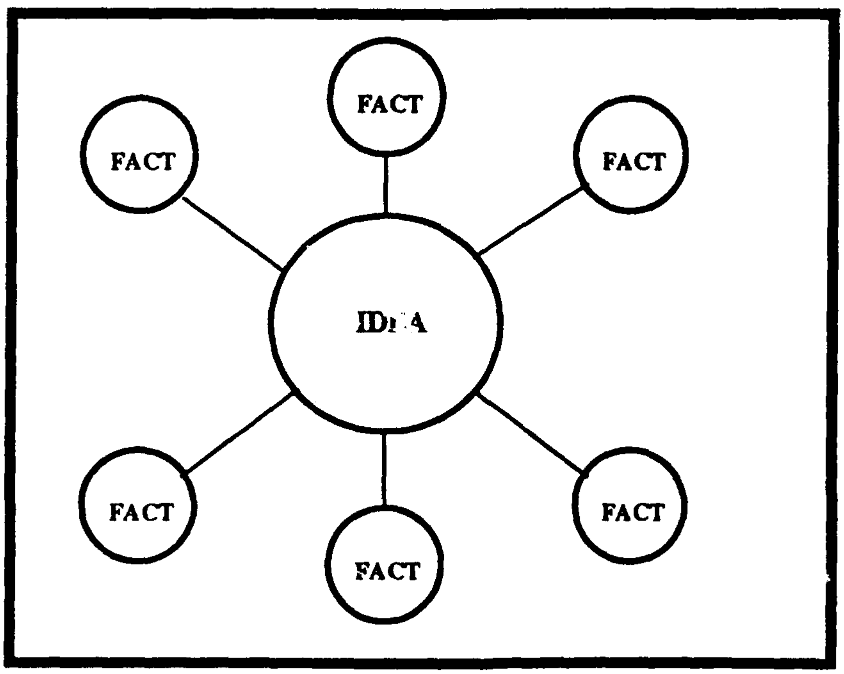

Figure 1. Example of a Web Diagram

- *Grids, pie charts, and graphs*: The frequency of some event is recorded in graphical form. Grids, pie charts, and graphs allow students to see trends in quantitative data.

- *Venn diagrams*: A set of overlapping circles is drawn as shown in Figure 2. Each circle represents some entity. Each entity has some uniqueness (e.g., A). The areas of overlap (e.g., ab, abc) represent shared or common characteristics. In Figure 2, circles A, B, and C might represent *mathematics, physics,* and *astronomy*. Venn diagrams allow students to sort information into multiple categories and compare various entities in terms of relevant characteristics.

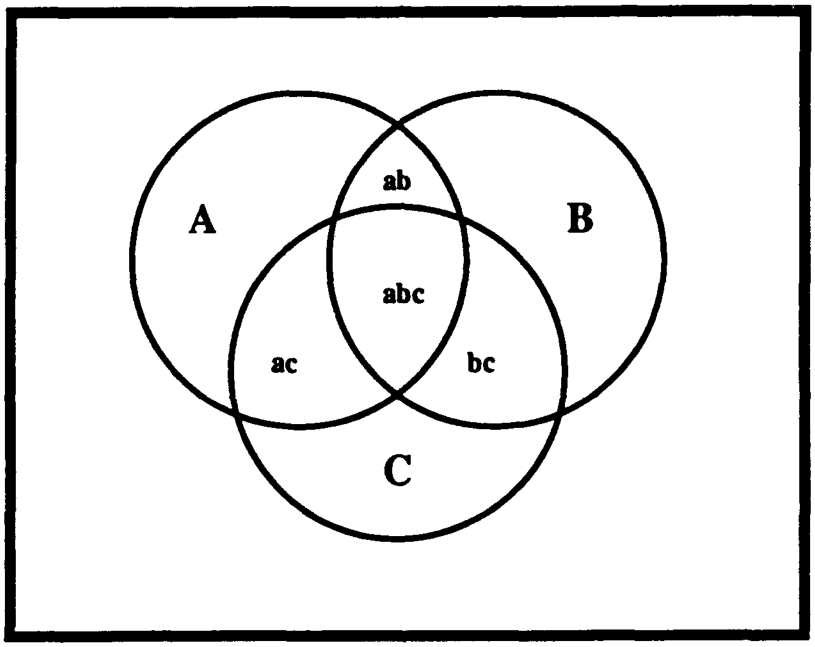

Figure 2. An Example of a Venn Diagram

- *Inductive towers*: Sets of facts are structured hierarchically under a theory. In Figure 3, the circles might represent a collection of observations about motion which successively build up to Newton's Laws. Inductive towers allow students to connect factual statements, build theories, and test predictions (see Figure 3).

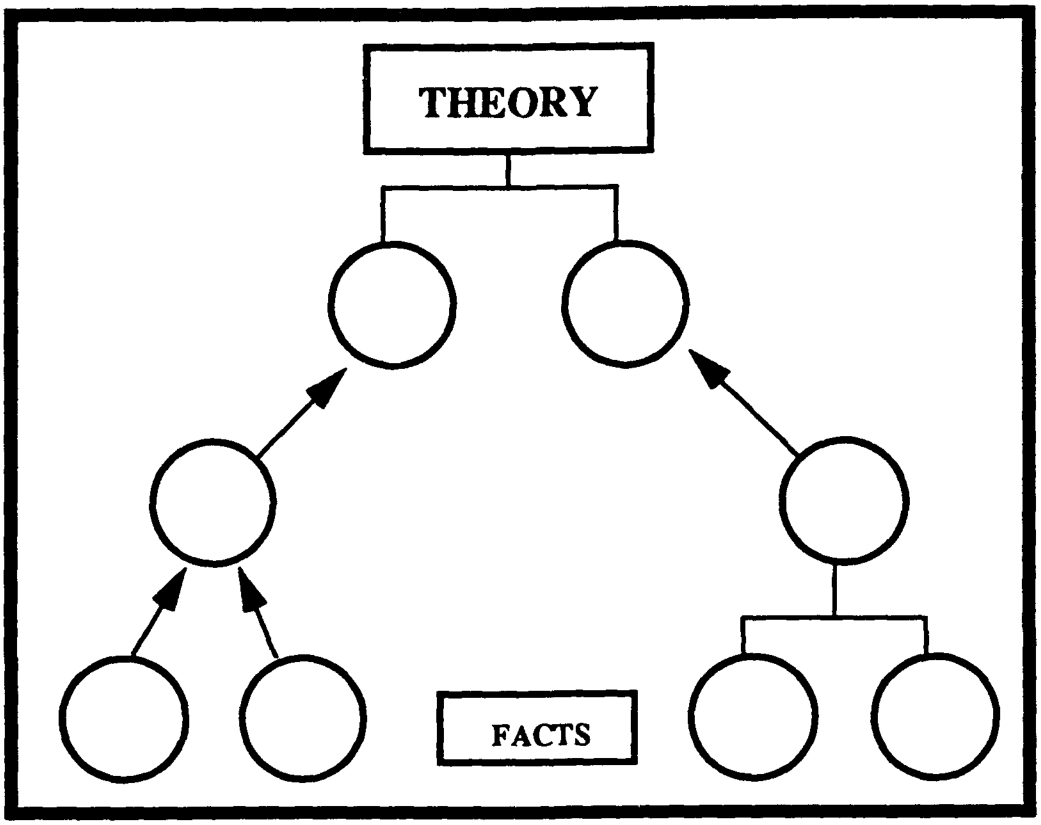

Figure 3. An Example of an Inductive Tower

Top-down organizers are deductively-based. They help students apply rules, test hypotheses, and make decisions. Clarke (1991) identifies the following top-down visuals:

- *Weighing scales, continuum lines, and pro/con charts*: Arguments for and against a theory, concept, or idea are charted and compared. These methods allow students to systematically examine the pluses and minuses associated with an argument.

- *Force field diagrams*: Antithetical forces are charted opposite one another. Force field diagrams allow students to see which side of an issue seems to have the most support.

- *Causal chains*: Sets of causes are linked to an observed outcome. Causal chains allow students to model processes and phenomena.

- *Decision trees and IF-THEN flow charts*: Sequential processes are charted. Decision trees and IF-THEN flow charts are like *road maps*. They allow students to follow a simple sequence to reach some outcome.

- *Concept maps*: Related ideas, concepts, and facts are arranged hierarchically. Connections between *nodes* are made explicit. Concept maps allow students to visualize connections between related concepts.

Concept maps have received the most attention in the literature by far. Therefore, this remainder of this section will focus on them.

The concept map is a specialized visual organizer designed to mimic hierarchical memory structures. Generally, concept maps consist of nodes and links. Nodes are concepts and links are relations. Nodes are arranged in order of inclusiveness. That is, the most general concepts are placed at the top of the hierarchy while more specific concepts or examples are placed at progressively lower levels of the hierarchy. Nodes are connected by links which indicate the nature of the relationship between concepts or examples (Novak, 1985). For example, a link between higher and lower-level nodes may have the descriptor, *characteristic of.* This means that the lower-level node is a characteristic of the higher-level concept.

The impetus for concept mapping, like advance organizers, comes from Ausubel's theory of meaningful learning. Ausubel asserts that meaningful learning occurs when new knowledge is accurately related to and subsumed by existing cognitive structure in a non-arbitrary, non-verbatim fashion (Ausubel, 1977). Supposedly, concept mapping accomplishes this goal by helping students to relate abstract, inclusive concepts with specific instances (Clarke, 1991). In a sense, the concept map is microcosmic representation of Ausubel's view of human cognition. In concept mapping, general and inclusive concepts subsume specific ones. That is, general and inclusive concepts are *progressively differentiated* or divided into smaller and smaller units. As this happens, the concept hierarchy grows, branching both vertically and horizontally. The same is true of human memory. Gradually, experience differentiates broad categories of knowledge. General, inclusive, and subsuming concepts are pushed to the top of the hierarchy while specific examples are pushed towards the bottom (Ausubel, 1977).

Purpose

The ultimate purpose of using concept maps and other visual organizers is to facilitate meaningful learning and promote metacognitive development. Supposedly, visual organizers accomplish these goals by mimicking innate thought processes, focusing on higher-order thinking skills, and taking advantage of the unique human capacity for visual learning (Cliburn, 1990). Concept maps can also be used as evaluation tools. When concept maps are used to evaluate domain knowledge, it is often

easy to detect where student misconceptions lie (Moreira, 1985; Zeitz & Anderson-Inman, 1992).

Summary and Evaluation of Findings

Visual organizers (e.g., concept maps) seem to support student comprehension and encourage the development of higher-order thinking skills (Clarke, 1991). Not surprisingly, Novak, Gowin, & Johansen (1983) found that higher ability students tended to be the most effective mappers. They also found that the use of mapping strategies facilitated novel task transfer over traditional learning conditions (Novak et al., 1983). Hienze-Fry and Novak (1990) did not find significant differences between mapping and non-mapping groups on measures of learning and retention. However, *error analysis* revealed that mapping helped to clarify learning by reducing the numbers of errors made by mappers (Heinze-Fry & Novak, 1990). Similarly, Lambiotte, Peel, and Dansereau (1992) found that concept mapping did not improve performance on a simple test of recall, but that it did improve higher-thinking skills.

Other researchers, such as Pankratius (1990), have found that concept mapping does result in superior achievement over non-mapping strategies. One possible explanation for this discrepancy lies in the fact that certain learner characteristics seem to mediate the relationship between concept-mapping and post-test achievement. For example, Stensvold and Wilson (1990) found that low verbal ability ninth grade students performed significantly better under concept mapping strategies than non-concept mapping students. Interestingly, this effect did not hold up for high verbal ability students (Stensvold & Wilson, 1990). The literature seems to suggest that requiring students to concept map does not, in and of itself, improve performance on simple tests of learning. It does, however, appear that mapping strategies facilitate higher-order thinking skills and promote long-term retention and transfer. Studies examining the relationships between concept mapping, learner characteristics, and achievement must be conducted.

Applicability to Intelligent Tutoring Systems

Visual organizers are well-suited for use in intelligent tutoring. The computer provides a unique medium for instantiating visual organizers. First, the logical and hierarchical structure of the concept map lends itself to computer-based diagnosis. Second, the computer can graphically represent several attempts at mapping some set of knowledge for a single student much like Collins' *abstracted reification*. Presumably, this form of reflection would facilitate metacognitive development. Third, the computer can easily model proper mapping skills.

Mnemonics

Definition

Mnemonics are memory devices which help the learner to encode and recall novel information (Davis, 1983). There are three general mnemonic strategies or ways to facilitate the encoding process:

- grouping strategies
- imagery strategies
- rhyming strategies

Information can be grouped or categorized according to some scheme. For example, if we have a list of animals to remember, we can group them into meaningful categories like carnivores, herbivores, and omnivores. Then, we can subdivide each category with specific examples. Grouping the animals facilitates the memory process by establishing meaningful ties between broad and specific forms of knowledge. This type of mnemonic utilizes a grouping strategy. Another grouping strategy involves arranging the first letter of the items in a list to form an imaginary word. For example, introductory algebra teachers often teach the FOIL method for simplifying certain algebraic expressions. Each of the letters of the mnemonic specifies an operation that the student is to perform. This form of grouping is probably the most common mnemonic strategy.

The second type of mnemonic coding strategy involves the use of mental imagery. Imagery strategies require the learner to associate the concepts to be learned with interesting images. The *one-bun, two-shoe, three-tree* strategy utilizes a common set of associations . The learner must initially learn the association scheme (i.e, one-bun, two-shoe etc.). Then, he or she may use the scheme to anchor novel information by forming visual associations between the information and the nouns listed in the scheme. In order to remember our list of animals, we would form connections between the first animal on our list and bun. Suppose the first animal was a lion. We could remember lion, the king of beasts, by imagining it wearing a bun as a crown. Next, we would pair the second item on the list with shoe, and so on. Another type of imagery mnemonic is called the *method of loci*. The method of loci requires that the learner associate concepts with locations. For example, we might remember our list of animals by associating each one with specific landmarks along a road that we commonly travel. The lion could be at the corner grocery store, the owl at the city park and so forth. To recall the list of animals, we would simply take an imaginary trip along our pre-memorized route.

The final type of mnemonic device is rhyming. Rhyming requires that either the teacher or student devise short rhymes which capture the target knowledge. *Columbus sailed the ocean blue, in fourteen-hundred and ninety-two* is a well-known example of this type of mnemonic.

Mnemonics, in short, are memory tools. They are designed to help us encode and

recall large quantities of information by tying that information to pre-memorized anchors.

Purpose

Mnemonics are devices which serve two purposes. First, they facilitate the transfer of knowledge from short-term to long-term memory. Second, they facilitate the recall of information from long-term memory (Davis, 1983).

Summary and Evaluation of Findings

Levin, Morrison, McGivern, Mastropieri, & Scruggs (1986) found that the use of mnemonic strategies resulted in superior post-test recall of science material for eighth grade students. Not only did subjects in the mnemonic condition outperform their counterparts, they were also aware of the benefits associated with the use of mnemonics. This suggests that they may possibly use them in the future. Another study indicated that the method of loci, or more specifically, the *spatial-arrangement mnemonic* also resulted in superior recall relative to other methods (Bellezza, 1983). Words were presented in same-arrangement and different-arrangement conditions. Different-arrangement conditions resulted in *distinctively arranged* sets of words embedded in maps. Bellezza found that distinctive word arrangements facilitated both recall and retention in college-age students. Therefore, it seems that emphasizing the uniqueness of a set of concepts by tying them to unique conditions results in superior recall.

Applicability to Intelligent Tutoring Systems

Computers would be an especially effective means of presenting graphical, imagery-based mnemonics to students. Static graphic images and animation could be used to promote mental imagery.

Learner Control

Definition

The term learner control is essentially self-explanatory; sometimes it is desirable to relinquish control of certain features of the instructional process to the student. Generally, the learner can exert control over four features of instruction: 1) lesson pace, 2) lesson content, and 3 & 4) the number and sequence of instructional events. Allowing learner control of instruction rests on the supposition that learners make good choices (Carrier, 1984). Unfortunately, they often do not. Therefore, before instituting a system of learner control, we must carefully consider the situation. The literature offers some findings which clarify this process.

Purpose

Learner control is often mentioned in conjunction with individualized instruction. Simply, if individuals are allowed to determine key features of the instructional process, then it is assumed that they will effectively tailor it to suit their needs. The promise of learner control is twofold. First, learner control should hypothetically increase achievement because students are allowed to tailor instruction to their needs. Second, learner control should contribute to positive student motivation and attitudes because students have the perception of control.

Summary and Evaluation of Findings

First, we will discuss the effects of learner and program control on student achievement. Program control refers to the more traditional approach of computer-based instruction. Specifically, the software, and not the learner, determines the characteristics of instruction. Kenzie, Sullivan, and Berdel (1988) found that learner control of content review in a computer based science lesson resulted in superior post-test achievement relative to program control. Other studies, however, have found contradictory results. For example, Carrier (1984) notes that complete learner control generally results in lower post-test achievement scores because learners select methods which they think will require less work, concentration, or time. Therefore, they opt for inferior methods of instruction and sacrifice achievement. Sometimes, given the option, they even opt themselves out of instruction all together.

The findings regarding the effects of learner control on achievement are mixed. One reason for this uncertainty is that a variety of learner characteristics seem to mediate the relationship between learner control and achievement. For example, older and more experienced learners seem to be better suited to learner control conditions than novice learners (Carrier, 1984). In a similar vein, Ross & Rakow (1981) found that students with low prior knowledge performed better under program control. Other studies have indicated that when the instructional material is simple that learner control is superior, but when the material is complex that program control results in higher achievement (Steinberg, 1989).

Research suggests that learner control of screen viewing does not affect achievement, but that learner control of the amount of material presented on the screen produced achievement gains (Steinberg, 1989). Lower ability students tended to choose higher density screens while average and higher ability students tended to choose lower density screens. Therefore, all students received the amount of information that they needed. High ability students did not have to sit through boring reviews of old material and low ability students had access to the additional information that they needed.

Other learner characteristics are tied to the effectiveness of learner control. An individual's locus of control is one such variable. Holloway (1978) examined locus of control, learner control, and achievement. He found that individuals with an internal locus of control performed better under learner control conditions. This finding makes

sense; individuals who are guided from within are more likely to prosper when they are free to make instructional choices.

Field independence is another psychological variable which appears to be related to the effectiveness of learner control (Carrier, 1984). Field independence is correlated with the cognitive restructuring of instructional stimuli. Field independents restructure a field of stimuli when it is beneficial to do so; they are less likely to accept a situation as given. They like to change situations to fit their needs. It seems logical, then, that field independents would prefer learner control because it allows them tailor certain features of the instructional stimuli to suit their needs. Field independents generally require more practice time than field dependents because they tend to use trial and error methods more often. Carrier, Davidson, Higson, and Williams (1977) allowed learners to choose expanded definitions, additional explanation, additional practice, or analytical feedback. Choice of options did not improve achievement. Field independent learners did choose more options than field dependent learners, however. Therefore, if nothing else, learner control allowed learners to tailor instruction to suit their needs.

Supposedly, learner control facilitates both student motivation and school attitudes. Ross and Rakow (1980), for example, found that learner control promoted positive attitudes towards learning. Steinberg (1989) summarized some of the key findings in learner control research. One point she makes is that, generally, learner control in computer-based instruction results in higher student motivation (Steinberg, 1989). Increases in motivation, however, are not usually reflected in achievement gains. In fact, as we have stated, the use of learner control with certain populations can actually reduce achievement. Student motivation is a desirable outcome in its own right, but it is probably not wise to sacrifice achievement for motivation.

Learner control is a complex issue which we have only briefly discussed here. However, we can offer the following guidelines regarding the use of learner control in intelligent tutoring systems:

- Use learner control with novices, low-ability students, or in complex domains with caution.
- Consider using learner control with advisement instead of pure learner control.
- Focus learner control on benign aspects of instruction to provide the learner with the perception of control and minimize achievement losses associated with poor learner choices.

Applicability to Intelligent Tutoring Systems

Learner control is essentially a computer-based technique. That is, learner control is primarily applied in computer-based instruction; it would be nearly impossible for a classroom teacher to allow each student to control important features of the

instructional process. Therefore, by definition, learner control is applicable to intelligent tutoring systems. The recommendations presented above should be followed, however.

Scaffolding and Fading

Definitions

Scaffolding refers to a process that gradually enables a learner to do something that he or she is not capable of doing alone (Palincsar, 1986)--like training wheels on a bicycle. Scaffolded instruction is based on Vygotsky's *zone of proximal development*. Vygotsky (1978) says the zone of proximal development is:

> *the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance, or in collaboration with more capable peer*

Vygotsky's definition of zone of proximal development reflects his two part theory of learning. Specifically, Vygotsky believes that learning has social and developmental components. Learning is a developmental process in that learners must navigate the zone of proximal development. One side of the zone represents the current state of knowledge while the other side represents a more mature, *developed* state of knowledge. Learning is a social process in that it requires interactions with those who hold the knowledge. Thus, scaffolded instruction is based upon a social and developmental theory of learning. Palincsar (1986) identifies the following attributes of the process of providing scaffolded instruction:

- It begins with the selection of a learning task that is emerging in the learner's repertoire but not yet mature.
- The task is evaluated to determine its difficulty.
- The teacher determines how to make the task easier, notes what parts of the task to accentuate in instruction, and determines how to sequence presentation.
- During instruction, the teacher employs modeling, questioning, and explanation to clarify the learning task.
- Instruction and learning occur in successive approximations.
- Emphasis is on student participation/interactive learning/collaboration.
- The purpose of evaluation in scaffolded instruction is to provide the teacher with an estimate of student knowledge and progress.

- Support is provided based on task difficulty and student knowledge.
- It is accompanied by *fading*.

Scaffolded instruction requires fading. Fading is accomplished by gradually withdrawing the metaphorical scaffold as the learner demonstrates increasing competence (Palincsar, 1986). Without fading, scaffolded instruction would be largely ineffective because some students would merely wait for the expert to solve the problem for them. The fading of support requires students to take an increasing amount of responsibility for learning and problem solving.

Purpose

The main purpose of scaffolded instruction is to facilitate the generalization of knowledge to less structured contexts (Applebee & Langer, 1983; Palincsar, 1986). Implicitly, scaffolding is also supposed to promote learning and retention through an interactive and nurturing learning environment.

Summary and Evaluation of Findings

Scaffolded instruction has proven successful in several empirical studies, although primarily with younger, lower ability populations. Palincsar and Brown (1984), for example, report that reciprocal teaching facilitates learning, retention, and transfer in seventh grade students classified as poor *comprehenders*. Palincsar (1986) reported similar findings. It is important to note, however, that these studies examined the effectiveness of reciprocal teaching as an instructional approach and not scaffolding itself. While the scaffolding/fading paradigm is a large part of reciprocal teaching, other characteristics of the approach may have confounded the results. Lajoie and Lesgold (1989) tested the effectiveness of an apprenticeship tutor on F-15 technical trainees' troubleshooting skills. They found that subjects who spent at least twenty hours working on SHERLOCK were as proficient in troubleshooting the test station as technicians with four years of experience (Lajoie & Lesgold, 1989). Again these findings do not represent the effects of scaffolding alone. Therefore, it is difficult to conclude with complete certainty that scaffolding is an effective tool although the preponderance of the evidence suggests that it is.

Applicability to Intelligent Tutoring Systems

Scaffolding is a useful instructional tool which can be instantiated in ITSs. The successful implementation of scaffolding in ITSs hinges on our ability to build complex and dynamic student models. The computer must be able to diagnose and respond to a variety of student behaviors.

Telling and Modeling

Definitions

There are three general ways in which teachers impart knowledge to students. First, and most simply, they hold students responsible for learning by requiring them to *do* something. Second, they *tell* students important information. Third, they *show* them skills or processes associated with some knowledge. This section discusses the characteristics of *telling* and *showing* as elements of instructional presentation.

Telling is often an efficient and effective means of transmitting information, although it can facilitate idiosyncratic learning, rote memorization, and diminish the importance of multiple perspectives (Schank & Jona, 1991). Telling requires the teacher to identify important information and pass it along to students. In this sense, the teacher plays an active role in the process while the student does not. Since the teacher identifies what information is important, telling is efficient; the student does not have to spend a lot of time sorting through irrelevant material. Unfortunately, telling is effective *only* when students actually understand what they are told. Often they do not. Therefore, telling content does not ensure learning (Winne, 1989). In fact, it can facilitate idiosyncratic and superficial learning of content because students only interact with the knowledge passively. They do not question it, they merely accept it. Telling is an appropriate instructional strategy under the following conditions:

- when only a small amount of information is presented
- when the lesson is ongoing
- when student requests information

Showing or modeling is often a more useful approach than telling. Five characteristics of modeling make it superior to telling alone. These characteristics promote meaningful learning, retention, and transfer (Anderson & Armbruster, 1990; Brophy, 1986; Shuell, 1988; Walberg, 1991):

- modeling requires both showing and telling of knowledge
- modeling is authentic
- modeling promotes multiple perspectives
- modeling promotes active student participation
- modeling affords students a wealth of instructional cues

Modeling requires an instructor to simultaneously demonstrate a skill or process and explain its purpose (Collins, 1988). Modeling, then, utilizes both the showing and telling of knowledge which provides the learner with more complete information than telling alone. Additionally, modeling takes advantage of our unique capacity as visual learners. Modeling is superior to telling, in this sense, because it includes the showing and telling of information. Telling, on the other hand, does not require showing.

Authenticity refers to realism in instruction. Instruction is traditionally situated in

the context of academia. Learners are led to believe that school knowledge does not have applications outside of the classroom. Modeling, on the other hand, situates knowledge in the context of its use. The instructor does not merely provide information, he or she demonstrates the application of that knowledge. The student receives explicit instruction in the real-world uses of knowledge. Therefore, superficial learning is minimized.

The use of multiple perspectives in instruction refers to the examination of more than one viewpoint for a given topic. Multiple perspectives in instruction increases the meaningfulness of learning by increasing the diversity of material covered. For example, an instructor might model alternative approaches to solving the same algebra problem. The student then sees two ways to solve the same problem. Even if the student fails to remember both strategies, the exercise has been useful because he or she knows that alternatives exist.

Modeling encourages more active learning than telling does, for two reasons. First, skills are demonstrated because students will be required to perform them. This encourages active participation because students usually want to perform well. Second, students often determine what will be modeled by asking questions and offering differing perspectives. Therefore, they have an active role in deciding what will be taught.

Finally, modeling offers students a plethora of instructional cues. Cues are timely prompts provided by the instructor which are designed to help the student overcome some problem. Walberg (1991) found an effect size of 1.25 for instructional interventions utilizing cues. In other words, students who received instructional cues did better than approximately 89% of those who did not receive cues. Not only does modeling provide the learner with obvious cues about how to do things; it also provides subtle cues about practical aspects of performance that an instructor might overlook if he or she were telling content.

Modeling is a flexible and comprehensive instructional method. It provides learners with a rich source of information which is simultaneously *authentic* and *diverse*. Generally, three benefits are associated with the use of modeling: 1) students see expert solutions to problems, 2) students can integrate what happens with why, and 3) invisible parts of the process are made visible (Collins, 1988).

Purpose

Telling and modeling are methods of instructional presentation. As such, they are designed to facilitate meaningful learning, retention, and transfer.

Summary and Evaluation of Findings

The effectiveness of modeling and telling are generally not tested independently. Rather, they are tested as components of larger models of instruction like cognitive apprenticeship and direct instruction. As mentioned previously, both of these larger models have been studied empirically and both seem to be effective instructional models.

Modeling, like cognitive apprenticeship, is a richer, more flexible, and more comprehensive approach.

Applicability to Intelligent Tutoring Systems

Both modeling and telling are applicable to intelligent tutoring systems. In fact, it is nearly imperative to use both of them because each is useful under different circumstances. Modeling should be used:

- at the beginning of a new lesson to structure subsequent instruction
- when the knowledge to be taught is general
- when the learner needs to be reminded of the *big picture*
- when the learner requests it
- early in instruction when fading has not begun

Telling should be used:

- during an ongoing lesson
- when the knowledge to be taught is specific
- when the learner requests it
- when fading of assistance is a system goal

Motivation

Like the proverbial horse, you can lead a student to class, but you can't make him learn. The purpose of investigating the topic of motivation was to identify what factors affect a student's willingness to learn, and what can be done--in the context of an intelligent tutoring system--to sustain and/or increase a student's level of motivation.

Definitions

Motivation can be defined as *that which gives direction and intensity to behavior* (E. Gagne, 1985). A basic assumption of motivational theories is that *all* behavior is motivated.

Motivation can be *intrinsic* or *extrinsic*. It is *intrinsic* if the goal or reward is the task itself. For example, in education, learning for the sake of learning is an instance of intrinsic motivation. Motivation is said to be *extrinsic* if external rewards or punishment must be used to influence behavior; because in this case, the goal is external to the task. Examples of extrinsic motivators include grades, prizes, smiles, and words of encouragement. In general, most theorists believe that intrinsically motivated learning is more desirable than extrinsically motivated learning (Davis, 1983). In practice, however, any type of motivation is better than none.

Motivation can be either a personality *trait* or a temporary *state* (Davis, 1983). As a *trait*, it is individualized, internalized, and closely related to attitudes regarding the

value of learning, aspirations, educational goals and self-esteem. Such individual differences are stable and lasting, and may influence not only schooling, but also many other spheres of a person's life. As a *state*, motivation is temporary and situational, depending on stimulating or dull events in the environment. Clearly it is these states of motivation over which the teacher has the greatest control.

Summary and Evaluation of Research

The research for this study concentrated on two areas: 1) factors affecting motivation, and 2) tools for assessment of motivation.

<u>Factors Affecting Motivation</u>

There are a number of factors which have been shown to influence motivation. These include: satisfaction of basic needs, curiosity, cognitive dissonance, desire for competence, need for achievement, attributions, locus of control, self-efficacy, nature of the goal, observational learning, orientation toward learning, gender, domain, training, and attitudes about computers.

Satisfaction of basic needs. Because all of the factors affecting motivation are related to the desire to satisfy some type of innate need, this term is a misnomer. However, it is used here to suggest that some needs are more basic than others, and that motivation is related to the level of urgency of the need that must be met. According to Maslow's (1970) *hierarchical need model*, human motivation is based upon level of need, beginning with basic physiological and security needs, progressing through the need for belonging, esteem, and knowledge, and culminating with the need for self-actualization. Maslow states that when a higher level need conflicts with a lower level need, the lower need takes precedence. Within the realm of education and learning, this simply means that a student's lower needs must be met before academic needs will appear. On the other hand, if the higher order needs are not met in the educational setting, the student will either barely *tolerate* the learning process or quit.

Curiosity. Curiosity is a source of motivation, because it leads to exploratory behavior aimed at reducing uncertainty (E. Gagne, 1985). Studies with children have shown that they tend to ask more questions about stories with high levels of uncertainty or novelty, than about stories with low levels of uncertainty or novelty (Berlyne and Frommer, 1966). From an educational point of view, this finding suggests that motivation to learn can be increased by exposing students to situations which may cause them to experience doubt or uncertainty.

Berlyne (1961) suggests several types of conceptual conflicts which may be used to arouse curiosity:

- *Doubt* is a conflict between the tendencies to believe and disbelieve. The use of hard to believe ideas will most likely cause arousal and the resultant exploration and information gathering aimed at removing the conflict.

- *Contradiction* is a conflict between those attitudes and beliefs held by the student and opposite statements proposed by the educator.

- *Perceptual incongruity* is an internally inconsistent sensory input.

- *Conceptual incongruity* is information about events and objects which contains incompatible elements (e.g., Alaskan Palm trees).

- *Confusion* or *ambiguity* stems from unclear ideas or incomplete information with behavior aimed at simplifying the ambiguous information.

- *Novelty* contains a degree of unexpectedness and uncertainty that stimulates interest and curiosity.

It should be noted that a very high level of arousal may produce poor performance. Optimum performance is achieved with a moderate level of arousal. However, this level may vary from individual to individual.

Cognitive dissonance. Like curiosity, cognitive dissonance is triggered by a conflict between ideas (Davis, 1983; Festinger, 1957). However, the term *curiosity* tends to be used to describe the impetus to explore; whereas the term *cognitive dissonance* tends to be used to describe the impetus to resolve a conflict by changing one's attitudes or opinions. For example, cognitive dissonance may arise when students' opinions differ from those of their parents, teachers, or society as a whole. When these conflicts occur, the tendency is to change attitudes and opinions toward credible sources which are respected, and away from sources which are not respected. The implication of cognitive dissonance for education is that the teacher or intelligent tutoring system designer should strive to maintain credibility and respectability.

Desire for competence. People seem to have an innate desire to develop skills and acquire knowledge (Davis, 1983; White, 1959). This desire is especially evident in young children, who often want to do things (like crawling or eating) for themselves. The implication for educators is that this desire should be encouraged, not stifled, whenever possible.

Need for achievement. The concept of a need for achievement helps explain the discrepancy between a student's ability and his actual classroom performance (Davis, 1983). This concept can be further broken down into *autonomously oriented* achievement motivation, which is based upon bettering one's previous performance; and *social-comparison oriented* motivation which is based upon comparison with others. Theorists suggest that autonomous achievement motivation develops early in a person's life and influences achievement as early as the second grade while social comparison achievement develops later--in about the fourth or fifth grades. Regardless of the student's age, each possesses simultaneous needs for achievement and failure avoidance.

McClelland (1985) points out that these needs are learned through environmental influences, and that the varying strength of these needs results in different behavior patterns in the classroom. For example, students with a strong achievement need will most likely prefer tasks of intermediate difficulty; whereas those whose fear of failure is greater than their need to succeed will most likely prefer either tasks that are very easy, guaranteeing success, or tasks which are obviously very hard for anyone.

These findings suggest that students with a low need for achievement and/or a high fear of failure should be identified and encouraged to set goals for themselves, and to accept moderate risk.

Attributions. In the 1970's and early 1980's a great deal of research was devoted to *attribution theory* (Weiner, 1979, 1980), which assumes that all persons are rational and have a need to understand their environment. This theory assigns a central role to the *content* of thought in motivation--specifically, whether the cause of success is attributed to *internal* factors, especially ability and effort, or to *external* factors such as task difficulty, luck or teacher bias. Some of the more noteworthy findings of this research as summarized by Davis (1983) are as follows:

- Young children tend to attribute success to high ability, high effort or both, which in turn increases their feelings of self-worth and strengthens their achievement motivation.

- Success in competitive situations enhances self-esteem and strengthens attributions of personal high ability.

- Attributions become more logical as children get older. Specifically, as children get older they tend to attribute their successes to effort and ability and to recognize that it takes more ability to accomplish difficult tasks as opposed to easy tasks.

- Minority students tend to focus on external attributions such as task difficulty and luck, which are a form of learned helplessness.

- Students are more likely to attribute success to effort and ability when they are engaged in individualized learning programs, where task difficulty is matched to the student's ability level.

- Attributions of college students seem to have a self-serving, ego protecting function in that successful students attribute their success to ability and good performance while those who perform poorly focus on external factors.

- Those who attribute success to either task ease or high ability have higher expectancy for success than do those who attribute success to luck or

effort.

- When students believe their success is due to a stable characteristic, they are more confident of future success because they believe the characteristic will exist in the future. In addition, when students perceive that their effort is a stable characteristic, they are more likely to raise their expectations for future success and will keep putting forth an effort.

The main implication of attribution theory is this: apart from a student's ability, his or her pattern of attributions can have a strong influence upon achievement. If students attribute their past failures to lack of effort, they are likely to try harder; whereas if they attribute their failures to lack of ability, they are more likely to give up. Similarly, if failure is attributed to bad luck, an individual is more likely to keep trying because things could change; whereas if they attribute failure to task difficulty, they are more likely to give up when they do not think task difficulty will change. Thus it is paramount that educators emphasize and encourage internal attributions such as effort as the route to success and point out that lack of effort and a focus on external factors leads to failure.

Locus of control. The concept of locus of control is closely related to attribution theory (Davis, 1983). People who tend to attribute success and failure to external factors such as luck or the teacher, are said to have an external locus of control. People who attribute successes and failures to their own ability or effort are said to have an internal locus of control. However, attributions may vary from situation to situation, whereas locus of control is more of a stable personality trait. That is, a student who consistently attributes her successes to luck probably has an external locus of control. Students with an external locus of control tend to be less motivated to make an effort in academics. Teachers need to be aware of these students and to encourage them to have higher self expectations.

Self-efficacy. Self-efficacy is used to refer to an individual's judgments about his or her ability to organize and implement actions in specific situations that may contain novel, unpredictable, and possibly stressful features (Schunk, 1984). Students' feelings of self-efficacy may affect their motivation to undertake a task, and the amount of effort and persistence they expend in completing it (Bandura, 1989). Meece, Blumenfeld, and Hoyle (1988) report that students who are concerned about their ability tend to use effort-minimizing strategies such as seeking frequent help, copying answers, and guessing at solutions. Reducing effort appears to be a defensive strategy used to protect feelings of self-worth, and to avoid the negative implications of low ability in the case of poor performance. By contrast, students who feel more efficacious not only exert more effort, but also have higher levels of intrinsic interest (Bandura and Schunk, 1981).

Individuals' perceptions of self-efficacy generally increase if they: 1) directly experience mastery of a goal; 2) observe others like themselves succeeding by perseverant effort; and 3) are persuaded by others that they are capable of success (Bandura, 1989). Teachers should be aware of some of the behavioral signs of low self-

efficacy, and be prepared to encourage students with low self-efficacy.

Nature of the goal. Certain properties of goals may also have an effect on students' motivation. For example, goals which are proximal (i.e., close at hand) tend to be more motivating than goals which are distal (i.e., far off). A study by Bandura and Schunk (1981) found that students encouraged to set proximal goals for themselves performed significantly better and had higher levels of self-efficacy for a particular task than students encouraged to set distal goals or who were not encouraged to set goals at all. Also, goals which are more specific are more motivating than general goals. And finally, assuming requisite skills, individuals tend to expend greater effort on difficult goals (Schunk, 1990).

Observational learning. Individuals tend to observe and imitate the behaviors of others, particularly those they respect or identify with (E. Gagne, 1985) Students will often watch and learn from the behavior of more successful or popular students, or from the behavior of their teachers or parents. Teachers can take advantage of this tendency by trying to get the more popular students to be academically involved, and by modeling appropriate learning strategies themselves.

Orientation toward learning. Some motivation researchers (e.g., Dweck, 1986) have made a distinction between *mastery* and *performance* orientations toward learning. Individuals with a mastery orientation seek to increase their competence--to master something new. Individuals with a performance orientation seek to gain favorable judgments about their competence or to avoid unfavorable judgments.

Dweck notes that these patterns can have profound effects on cognitive performance. A mastery orientation is characterized by challenge seeking and persistence in the face of obstacles. A performance orientation is characterized by challenge avoidance and low persistence in the face of difficulty (Dweck, 1986).

From a teaching point of view, challenging tasks are often the best way to develop students' capabilities. Students with performance orientations are less likely to benefit from challenges. Teachers should help such students to develop a mastery orientation by encouraging them to pursue challenges and then teaching them to attribute failures to effort or strategy, rather than ability (Dweck, 1986).

Gender. Bright girls, as compared to both bright boys and less bright girls, seem to demonstrate shakier expectations, have lower preference for novel or challenging tasks, more frequently attribute failure to lack of ability, and more frequently debilitate in the face of confusion or failure (Licht & Dweck, 1984; Stipeck & Heffman, 1980). Lewis and Cooney (1987) also state that female students tend to perform best when the comparison is based upon their own performance as opposed to males who tend to perform best under situations when comparison is in a social context. It is not clear why this tendency exists, but in any case, teachers should be aware of it, and be prepared to encourage girls accordingly.

Domain. Motivation can also vary with domain. A study by Young, Arbreton and Midgley (1992) examined motivation and cognition in four academic domains: math, English, science and social studies. They found that among the different domains, students exhibit different goal orientations (performance vs. mastery orientation) and strategies (surface vs. deeper level of cognitive strategies). Students are more likely to be mastery oriented in both math and science in comparison to either English or Social Studies. Students' reported use of deeper processing strategies was significantly higher in English than in math, science and social studies, and deep processing was used significantly less in social studies than in all other content areas. In all areas there is a significant negative relation between mastery orientation and surface processing strategies and between performance orientation and deep processing strategies.

Students were most likely to hold a performance-focused orientation in social studies than in other content areas and were least likely to hold such an orientation in math and science. Finally, students were significantly more likely to use surface level strategies in social studies than in all other subjects, and they were less likely to use these types of strategies in science.

In sum, motivational techniques should take domain specificity into account. Knowledge of which types of strategies are most likely to be used in specific content areas can be used to guide the selection of techniques.

Training. There is evidence to suggest that students can be taught to change demotivating or debilitating thought patterns. Klein and Freitag (1992) utilized Keller's ARCS method to design a booklet which provided students with information about motivation, examples, practice and feedback on how to make instruction relevant. The booklet was designed to be self-paced. Results indicate that students who were given self-motivational training significantly rated instructional tasks as having more relevance than students not given this training. These results were true for both immediate and delayed training effects.

Tools for Assessment of Motivation

Harter (1981) developed the Scale of Intrinsic Verses Extrinsic Motivation in the Classroom. This scale assesses the degree to which children manifest an intrinsic interest in learning, view themselves as being curious, and show a preference for challenging work or for opportunities to master material independently. Ames and Archer (1988) developed a questionnaire which examined the areas of goal orientation, learning strategies, task challenges, attitudes towards class, causal attribution and perceived ability. In addition, many personality tests include subscales for various aspects of motivation; and tests exist for some of the factors listed in the previous section (e.g., locus-of-control). However, there is no widely accepted instrument for a thorough assessment of motivation in the classroom.

Evaluation of the Research

To enable an intelligent tutoring system to keep students motivated, developers need to know what to monitor, how to monitor it, and how to respond with appropriate interventions. The research literature on motivation at least partially answers the *what to monitor* requirement. However, it is less helpful in prescribing *how to monitor* motivation and *how to keep it high.*

In terms of what to monitor, the literature has identified a number of factors which affect motivation. However, the terminology is spongy. Often different constructs, such as self-efficacy and the idea of having a performance orientation toward learning, seem to be describing the same thing. Assessment would be more efficient if the factors were more distinct, and ITS developers knew which factors influence motivation the most.

Without knowledge of which factors influence motivation the most, it is impossible to know how to monitor it. The fact that there is no widely accepted instrument for measuring student motivation available confirms this. Such an instrument needs to be developed. Perhaps this instrument could take advantage of some of the test presentation and data collection capabilities of the computer.

Finally, the literature gives little guidance about how to sustain and/or increase motivation in specific situations. There is plenty of general advice, such as *engage curiosity* and *encourage effort rather than ability attributions*. However, there is relatively little precise guidance about what to do in, for example, a situation where a student has a low need for achievement, low self-efficacy, and an internal locus of control. Most studies of factors affecting motivation examine only one factor at a time. There needs to be more research on how the factors interact.

There also needs to be more research on ways of sustaining motivation over a long period of time. For example, some techniques, such as those which pique curiosity, may affect state motivation, but not trait motivation. Perhaps in some cases, motivating and demotivating factors effectively cancel one another out in the short term, but have lingering effects in the long-term; for example, a student with a high need for achievement (e.g., to please his parents), but low self-efficacy may perform well in school, but ultimately fail to reach his full creative potential. Also, use of some techniques for increasing motivation (again, such as those which pique curiosity) may lose their effect over time, as students get used to seeing them.

Applicability to Intelligent Tutoring Systems

The current research yields broad prescriptions which could help to increase motivation in many cases. It is probably informative enough for traditional computer-assisted instruction, which relies mostly on the developer's ability to anticipate the student's needs anyway. However, it is probably *not* informative enough for intelligent tutoring systems, which offer the capability of *targeting* instruction to specific student

needs. Intelligent tutoring system development (as well as education in general) would benefit from a unifying theory of motivation, which explains what factors affect motivation and the extent to which they add to or mitigate each other's effects.

Areas for Assessment

A major goal of intelligent tutoring systems is *individualization* of instruction. The hope is that by tailoring instruction to individual students' needs, all students can achieve certain minimum learning requirements, and every student will have the opportunity to fully develop his or her potential.

Of course, individualization requires some knowledge of the individual. One approach to individualizing instruction involves representing individual students' knowledge as it develops (Shute, 1991). This approach generally involves developing *bug libraries* or other student models (Brown & Burton, 1979). Although this can be an effective approach, it is costly to implement. In addition, effective instructional decision making may involve more than knowing what the student knows. It may also involve knowing about certain personality characteristics of the learner, such as self-efficacy, motivation, and cognitive style.

Another approach to individualizing instruction involves the assessment of incoming knowledge, skills, and personality characteristics (Shute, 1991). These incoming characteristics can then be used to determine appropriate instructional treatments.

The two approaches are not mutually exclusive. In fact, they could be complementary. Pre-assessment can be used to determine the overall approach to instruction, including the structure of teacher-student interactions, and the manner and sequence in which new information will be presented. Student models can be used to monitor student understanding *play-by-play*, as it were, which can be helpful for decisions such as what type of teaching action to take next, or what topic to cover. Student models may also be used to make adjustments to the approach initially determined by pre-assessment.

This section will focus on identifying the types of information needed for assessment.

Summary and Evaluation of Research

There are two approaches to identifying the types of information needed for assessment. One way is to identify the information expert human teachers attend to while interacting with their students. Examining what teachers look for and how they use this information could provide clues about the types of information that a computer should assess both before and during instruction.

A second approach is to study how particular psychological constructs (e.g., intelligence, motivation, cognitive style) affect learning. Assessing aptitudes or personality traits could then allow the computer to target instructional treatments to particular types of individuals. The following sections briefly review studies using both types of approaches.

Studies of teachers. One would expect that teachers utilize many different types of information in making instructional decisions. However, if this is so, it is apparently not at a conscious level. Studies of teacher behavior have shown that teachers have difficulty identifying what variables they attend to and what principles guide their instructional decision-making. Only two variables are routinely identified by teachers as having an impact on their decision making (ability and motivation) and even these constructs mean different things to different teachers (Corno & Snow, 1986).

What teachers do attend to is their mental teaching *scripts* (Borko & Shavelson, 1990) These scripts consist of well-established routines for various teaching activities (one commonly used script, for example, is the pattern of *structuring*, *soliciting*, *responding*, and *reacting*). Researchers have found that in general, classroom teachers only engage in interactive decision-making when they are forced by problems or unexpected events to abandon their scripts (Borko & Shavelson, 1990; Shavelson & Stern, 1981; Clark & Yinger, 1979).

The needs of intelligent tutoring systems development have spawned a number of studies of human tutors in one-on-one situations (e.g., Merrill, Reiser, Ranney, & Trafton, 1992; Schoenfeld, Gamoran, Kessel, & Leonard, 1992; Fox, 1991; Galdes & Smith, 1990; Yee, 1989; Littman, Pinto, & Soloway, 1985; Collins, Warnock, & Passafiume, 1975). These studies have been much more successful at identifying the types of information attended to by human tutors. However, although these studies make the logic behind these tutors' instructional decision-making more evident, it is not clear if the decisions made were *the best* in an absolute sense or simply the best the tutors studied could think of.

In conclusion, deriving information from human teachers may not be the best approach to determining what information to assess. First, in some cases it may be difficult to get them to precisely identify what types of information they use. Second, even if it is possible to discover this information, it is still necessary to evaluate whether or not this information is 1) helpful in instructional decision making; and 2) feasible for intelligent tutoring system implementation.

Studies of psychological constructs. The other approach to identifying information for pre-assessment is to study the impact of various psychological constructs on teaching effectiveness. For example, Shute (1991) found an interaction between an exploratory learning style and type of learning environment. Specifically, high exploratory learners learned better from an inductive learning environment; whereas low exploratory learners learned better from a structured, explicit learning environment.

Table 4 lists some pre-assessment variables which have been frequently mentioned in discussions of adaptive instruction. It also gives their definitions, what research has shown about their relationship to learning, and a rough assessment of their applicability for implementation within intelligent tutoring systems.

The table indicates four variables judged to be particularly relevant to implementation in intelligent tutoring systems. Some comments on these variables follow.

Intelligence is consistently the best predictor of academic success (Corno & Snow, 1986; Hakstian & Gale, 1979). Likewise, educational history is helpful in determining at what level instruction should begin. Students with high levels of prior knowledge or intelligence could be bored if instruction is too easy; students with low levels of both may become frustrated if instruction is too hard. Much research has been conducted in these areas, especially to determine what types of instruction are most beneficial for students of higher or lower ability. However, there seems to be some disagreement over whether measures of past achievement or measures of aptitude are better for this purpose.

The research also strongly indicates that self-efficacy is related to performance. Zimmerman (1989) found that increases in self-efficacy are related to improved performance even while controlling for ability level. Other researchers (Carlson and Grabowaki, 1992; Bandura, 1989) have found that domain-specific measures of self-efficacy provide more accurate assessments. Self-efficacy is particularly appealing for implementation within intelligent tutoring systems because it can be reliably measured, and it can be improved through various interventions.

There are many dimensions to the construct referred to as *cognitive style* (e.g., field independence/dependence, reflective/impulsive, scanning/focusing, leveling/sharpening); however, not all have well-documented effects on learning. However, research on field independence/dependence has been going on for a longer time than research for the other dimensions, and tends to be of a higher and more consistent quality. Most of this research suggests that field independence/dependence can be a valuable variable for pre-assessment, and that individuals from the two groups do pick up information differently (in terms of how they perceive the world and how they learn). However, researchers need to take a closer look at people who score at or close to the mean. At least one study (Meng & Del, 1991) suggests that these *field-intermediates* differ from the extremes, and that they need different instruction (rather than something in-between) from the other two groups.

In conclusion, some clear connections have been established between individual constructs and performance which should help in deciding how to individualize instruction. However, in most cases the influence of particular constructs has been studied in isolation. There need to be more studies which examine the interactions between specific constructs and instructional treatments, or between combinations of constructs.

It would be ideal if the computer was able to figure out for itself which variables seem to have the greatest impact on learning for each student. This would be an excellent area for the application of machine learning concepts.

Applicability to Intelligent Tutoring Systems

Research about assessment variables is very applicable to intelligent tutoring systems development. However, knowing what needs to be assessed is just one part of the problem. Another part is to figure out how to assess these variables on the computer, and with minimal loss in instructional time. Yet another part is developing principles for how the assessment information will be used in instruction. It is important to establish that the uses of the information will be worth the trouble of gathering it.

Even if perfect adaptation of instruction to the student (so as to always maximize performance) were possible, it is not clear if it is desirable. There is some evidence to suggest that *mismatching* educational treatments to learner characteristics may stimulate flexibility and creative thinking (Messick, 1984). It is important to remember that judgments about educational programs ultimately require decisions to be made about social values.

Table 4. Potential Variables for Pre-Assessment.

Variable	Definition	Instructional Decisions Impacted	Applicability
Educational history	Background knowledge in the domain to be taught	What to teach; whether or not to use a direct instruction approach (Corno & Snow, 1986)	***
Intelligence	Score on various recognized measures of IQ	What to teach; whether or not to give cognitive strategy training; whether or not to use discovery learning; what degree of learner control to allow (Corno & Snow, 1986; Frederickson, 1984)	***
Self-efficacy	An individual's personal judgment of performance capabilities in a given domain (Schunk, 1984a)	What types of instructional motivators to use (Schunk, 1984b)	***
Cognitive style - Field independent, dependent, or intermediate	Degree to which an individual can distinguish a single figure within a larger, more complex figure. Often determined by score on Group Embedded Figures Test (Witkin, Oltman, Raskin, & Karp, 1971)	Whether or not to give learning strategies training (on tasks such as taking notes); to what degree should structure of a lecture/lesson be made clear; what type of advance organizer to provide (Meng & Del, 1991; Frank, 1984)	***
Motivation	That which gives direction and intensity to behavior (E. Gagne, 1985)	Whether or not students need to be taught self-motivation strategies (Klein & Keller, 1990)	**
Test anxiety	Anxiety about taking tests	Whether or not to give training on how to deal with anxiety; whether or not to provide competitive learning situations (Naveh-Benjamin, 1991; Weinstein & Mayer, 1986)	**
Cognitive style - reflective or impulsive	Degree to which an individual thinks over an action before taking it. Generally measured by Matching Familiar Figures Test (Kagan, 1965)	Whether or not to give training in effective problem-solving strategies; whether or not to give training in analytic reading strategies; whether or not practice using a random schedule (Heckel, Allen, & Stone, 1991; Walczyk & Hall, 1989; Jelsma, Van-Merrienboer, & Jeroen, 1989)	**
Locus of control - internal, external	Degree to which individuals feel they have control over their environment.	Whether or not to use direct instruction; whether or not to encourage development of internal locus of control (Klein & Keller, 1990)	*
Learning style - accomodator, diverger, converger, or assimilator	Degree to which an individual prefers active or reflective, and concrete or abstract modes of learning. Generally measured by Kolb's Learning Style Inventory (Kolb, 1984).	No significant effects were found in studies of the relationship between learning style and effective learning (Billings & Cobb, 1992; Karrar, 1991; Larsen, 1992)	*

*** Very applicable, easy to implement

** Applicable, may be somewhat difficult to implement

* Could be applicable, uncertain about implementation

Use of Questions

Because intelligent tutoring systems do not have eyes or ears, the best way for them to get information about students is to ask. Therefore knowledge about the appropriate use of questions is especially important for ITS development.

Definition

Questions can have several functions. The most common function is to get information, which in instructional contexts generally means information about what the student knows. However, questions can also be used to promote higher-level cognitive processes, to gain attention, or as an indirect command (e.g., "could you pass me the salt?"). The focus in this section will be on instructional uses of questioning.

Review and Evaluation of Research

The review included literature on question taxonomies and formats. There are numerous taxonomies which can be used for classifying questions (see Gall, 1970, and Graesser, 1992, for examples), but the most well-known one by far is Bloom's taxonomy. This taxonomy consists of the following levels: Knowledge, Comprehension, Application, Analysis, Synthesis, and Evaluation (Davis, 1983). These six levels describe progressively higher levels of cognitive processing. Figure 4 lists some sample questions for each level of the taxonomy.

Knowledge - What is the formula for computing the standard area of measurement?

Comprehension - Examine the graph and determine how many items must be added to a 50-item test to increase its reliability from 0.60 to 0.80.

Application - Compute the standard error of estimate for a test having a correlation of 0.70 with a criterion having a standard deviation of 10.

Analysis - Differentiate between a classroom achievement test and a standardized achievement test in terms of what each measures and how each is used.

Synthesis - Formulate a theory relating interest to personality, citing appropriate supporting research evidence.

Evaluation - Evaluate the criticisms of Ralph Nader and Allen Nairn concerning the Scholastic Aptitude Test (SAT).

Figure 4. Sample Test Items for Each Level of Bloom's Taxonomy (from Aiken, 1991).

Although Bloom's taxonomy neatly expresses the hierarchical nature of knowledge, it does not capture the full range of reasons why a question might be asked. Gall (1970) identifies some worthwhile question types which are not covered:

- questions which cue students to elaborate on a weak response to a previous question (e.g., "Can you tell me more?" or "What do you mean by that?")

- questions which stimulate a student's curiosity or sense of inquiry (e.g., "What would you like to know about dinosaurs?")

- questions which guide a student's learning of a skill (e.g., "What do you think we should do next?")

Intelligent tutoring systems could potentially use all of these question types. However, the research lacks guidance about when to use which type. There needs to be more research on how to sequence question types (e.g., how do you know when to start asking questions at a higher level?), and when to use the various types of questions.

The literature on question formats covers when and how to use written formats such as true-false, multiple choice, and essay questions (Aiken, 1991; Davis, 1983), as well as effective classroom questioning strategies (Ornstein, 1988; Otto, 1991). Although this literature contains helpful guidance about how to ask questions, much of it is geared toward classroom situations rather than computer-based teaching situations. For example, most classroom questions are either oral (i.e., in the context of a lesson) or paper-and-pencil based. Computers are not good at dealing with oral questioning, and they are capable of much more than the standard multiple-choice or true-false formats. Questioning on the computer needs to be looked at in a completely different way from questioning in the classroom.

Applicability to Intelligent Tutoring Systems

The problem with intelligent tutoring systems is that they cannot deal with open-ended question formats as easily as human teachers can. During instructional presentations, human teachers routinely obtain information about how much students understand simply by asking them to answer questions or provide explanations. With an intelligent tutor, the same process would be cumbersome in terms of both data input (the student would probably have to type) and answer analysis (computers' natural language processing capabilities are still very limited). In addition, human teachers can gather some information simply by observing their students; whereas an intelligent tutoring system would have to ask a student in order to get input.

Although this problem is not insurmountable, further research needs to be conducted on ways of presenting and assessing knowledge via the computer. For example, one capability that computer-based tutors have that human teachers lack is the ability to provide interactive games and simulations. For certain teaching situations,

perhaps students can be required to perform continuously. This would allow the computer to gather the data it needs, and it can interrupt when the student appears to need help (or to praise the student). From a teaching point of view, this would represent a paradigm shift--from a format where the teacher does most of the telling with pauses for student performance, to a format where the student does most of the performing, with pauses for instructions from the teacher.

Feedback

Definition

Broadly speaking, instructional feedback can be anything a teacher does in response to a student comment or action. Even if a teacher does nothing, his or her inaction can be construed as a type of feedback, because it sends a message to the student (e.g., "You're doing okay so far. Keep going."). Or if a student is in the middle of performing a task, giving feedback may involve first interrupting her, then correcting or praising her.

In practice, however, people usually think of feedback somewhat more narrowly. In studies of feedback in traditional computer-based instruction, for example, feedback is typically viewed as how the computer responds after the student has answered a question (Wager & Wager, 1985). The pattern is: computer asks question, student answers, computer gives feedback. Perhaps this is because traditional computer-based instructional systems are only capable of giving feedback in this manner.

Because intelligent tutoring systems have more sophisticated capabilities than traditional computer-based instruction, ITS developers and researchers should take the broader view of feedback in planning how to use it in their systems. However, findings from research which takes the narrower view are still very applicable.

Purpose

Feedback can serve two functions during instruction (Wager & Wager, 1985). First, it can motivate the learner. Second, it provides information about the correctness of the learner's responses. It should also be noted that poorly constructed feedback may produce the opposite outcomes.

Summary and Evaluation of Research

The review of the literature focused primarily on how various elements of feedback (such as amount of detail or timing) affect performance, anxiety, confidence, and learning efficiency. These findings are summarized in Table 5 (pages 41-45). The left-most column lists elements of instruction which could be included in or with feedback presentation, such as:

Level of detail

- no feedback
- knowledge of results (KOR) - whether a response is correct or incorrect
- knowledge of the correct response (KCR)
- answer until correct (AUC) - the student has to keep answering the question until he gets it right
- elaborated - includes explanation. The content varies, but usually involves either telling the student why her answer was wrong or right, or giving her information which will help her to get the answer right in the future.
- natural - results of a student's actions are displayed automatically, as in a simulation
- adaptive - any of the above, depending on certain situational criteria

Timing relative to the student's response

- immediately after
- delayed - amount of delay may range from seconds to days
- when requested - learner control of feedback

With other instructional support available (e.g., lesson material)

- available
- not available

With performance feedback (e.g., scores) available

- available
- not available

Personalization (e.g., addressing the student by name)

- available
- not available

The top row of the table lists factors which might be affected by the presence or absence of the elements in the left-hand column. These include task performance, non-performance factors such as anxiety and confidence, and overall lesson efficiency (i.e., the time it takes to achieve a certain performance result). The cells in the table list findings from the literature about how the elements of feedback affect these factors.

Some general comments on the findings: First, the research on the required amount of detail in feedback is not very conclusive. It seems safe to conclude that any amount of feedback is better than none at all in terms of improving performance. But it is not clear how the various levels of detail compare to one another. In general, more information does not appear to hurt student performance (Salas & Dickinson, 1991). But if the additional information does not actually get used, then including it may be a waste of both lesson time and development time (Clariana, Ross, & Morrison, 1992).

Ultimately, the optimal amount of information in feedback may depend on the

learner. Low ability or low achieving learners may benefit from more explanation in feedback (Collins, Carnine, & Gersten, 1987); however, they also need to be taught how to utilize feedback information effectively. High ability learners seem to use knowledge of results feedback more effectively than low ability learners (Hansen, 1974). But too much information for these types of learners may inhibit them from learning to reason for themselves (Clariana, Ross, and Morrison, 1992).

Surprisingly little is known about how feedback form or content affects learning (Wager & Wager, 1985). There are at least three reasons for this. First, feedback can take many different forms, ranging from simply stating that an answer is correct or incorrect, to revealing the correct answer, to allowing students to keep trying till they get the correct answer, to providing explanations about why certain answers are right or wrong. Explanations can be long or short, reviews or restatements, text-based or pictorial. Without specifying the form of feedback used, it is impossible to speak meaningfully about the effects of feedback.

One interesting example of how the content of feedback affects how a study should be interpreted is a study by Hansen (1974) on the effect of feedback on state anxiety. Hansen predicted that use of feedback should reduce learners' levels of state anxiety, and that high anxiety state subjects would make fewer errors under the feedback condition than under the no-feedback condition. He found that in general, feedback did decrease levels of anxiety. However, high anxiety subjects actually made *more* errors under feedback than under no-feedback conditions. It turns out the feedback condition used in his study consisted only of telling subjects if their responses were correct or incorrect (KOR feedback). It is easy to imagine that an already anxious subject might become more anxious after missing a question and not knowing *why*. Therefore Hansen's findings about the effect of feedback on state anxiety should be qualified to apply for KOR feedback only.

The second reason why little is known about how the content of feedback affects learning is that there are many factors which must be considered in evaluating the effects of feedback. These include the difficulty level of the material to be learned, the characteristics of the learners, and the context of the study (i.e., lab or school). Why feedback is found to be effective or ineffective often depends on the manner in which it was evaluated. For example, many studies of feedback are conducted in a laboratory environment (Kulik & Kulik, 1988). These types of studies have consistently shown that feedback results in better retention if it is given after a delay of as much as 24 hours (Sturges, 1978; Rankin & Trepper, 1978; Sassenrath, 1975). However, in laboratory studies, there is usually no additional instruction, and the treatment questions are identical to the post-test questions. And in fact, in studies conducted in more realistic learning situations, students almost always perform better when they receive immediate rather than delayed feedback (Kulik & Kulik, 1988).

Finally, the terminology used in feedback research varies from study to study. Even the definition of the word *feedback* varies. For example, some studies consider stating an answer to be correct or incorrect to be feedback, while others treat it as a no

feedback condition. Although variations in terminology may not lessen a study's contribution, they do make the findings less accessible.

Applicability to Intelligent Tutoring Systems

The existing research on feedback is clearly applicable to intelligent tutoring systems. However, much of it was conducted with traditional paper-and-pencil type tests. Even the research that was done using the computer tends to be with traditional text-based question formats. There needs to be more research on effective uses of the types of feedback unique to intelligent tutoring systems. That is, there needs to be more research on ways of tailoring feedback to the learner, since ITSs have the capability of being able to individualize instruction. And there also needs to be more research on effective use of feedback for the types of assessment capabilities (i.e., uses of games and simulation to assess performance) which are unique to the computer.

Table 5. Feedback Research Summary.

Element	Impact on Performance Factors	Impact on Non-Performance Factors	Impact on Learning Efficiency	Comments on Findings
Content - No feedback	Clariana, Ross, & Morrison (1992) concluded that in general, any level of feedback seems better than none. However, Hansen (1974) found that high anxiety state learners performed better under the no-feedback condition than under a KOR feedback condition.	Hansen (1974) and Sturges (1978) both found that no-feedback conditions increases state anxiety relative to KOR feedback conditions.	No studies identified. Probably depends on the complexity of the lesson and the ability or background knowledge of the learner.	Well-replicated.
Content - KOR	Hansen (1974) found that KOR feedback aids high ability learners, but impairs low ability learners. Another study shows that KOR feedback is less effective than forms of feedback which provide additional information (Salas & Dickinson, 1991).	Generally reduces state anxiety in comparison to no feedback at all (Hansen, 1974)	No studies identified, but probably depends on complexity of the lesson and the ability or background knowledge of the learner.	Not a lot of research on this form of feedback, probably because people do not usually expect it to be instructionally effective.
Content - KCR	Significantly more effective than AUC (Clariana, 1990). Also more effective than some elaborated formats, and as effective for others (Kulhavy, White, Topp, Chan, & Adams, 1985).	No significant effect on state anxiety (Sturges, 1978).	More efficient than AUC for low ability learners (Clariana, 1990). Also more efficient than several forms of elaborated feedback (Kulhavy, White, Topp, Chan, & Adams, 1985).	Amount and quality of research in this area seems satisfactory. This type is widely regarded as the minimal acceptable amount of feedback.
Content - AUC	Significant effect for low achievers when combined with removing feedback from screen (Tait, Hartley, & Anderson, 1973). Also significantly more effective than KCR as similarity between lesson and post-test questions decreases (Clariana, Ross, & Morrison, 1992).	No studies identified.	No studies identified.	This type of feedback is often not used the way it is tested in research; i.e., learners usually get a second try <u>and</u> a hint or explanation, rather than just being told to try again until they get it right. However, these studies suggest that the act of having to answer a item again may increase depth of processing for that item (Clariana, Ross, & Morrison, 1992).

Table 5. Feedback Research Summary (cont.)

Element	Impact on Performance Factors	Impact on Non-Performance Factors	Impact on Learning Efficiency	Comments on Findings
Content - Elaborated	Merrill (1987) found no significant difference between elaborated feedback emphasizing key attributes of concepts to be learned and KCR feedback. However, Salas & Dickinson (1991) found that elaborated feedback which includes a mnemonic to help students remember key attributes of a concept was significantly more effective than KOR feedback, and the most effective form of elaborated feedback. Collins, Carnine, & Gersten (1987) found elaborated feedback was significantly more effective than KCR feedback for learning disabled and remedial high school students. McKendree (1990) found that students receiving elaborated feedback about the goal structure of geometry problems performed better than those students receiving KOR feedback or elaborated feedback which explained why their answer was incorrect.	Subjects receiving elaborated corrections were significantly more confident about their ability to perform the trained task than students receiving KCR feedback only (Collins, Carnine, & Gersten, 1987)	No significant difference in lesson completion times between elaborated and KCR treatment groups (Collins, Carnine, & Gersten, 1987)	The main finding seems to be that elaborated feedback is not necessarily either efficient or effective. Helpful elaborated feedback, whatever its content, provides information which the student needs and can use Just because there are more words on the screen does not mean that they will be processed meaningfully.
Content - Natural	As effective as KOR or elaborated feedback when used for appropriate tasks and with learners who know how to use it (Park & Gittelman, 1992).	No research identified.	Significantly more efficient than KOR feedback in terms of time required to complete a lesson.	Effective use of natural feedback probably depends on the nature of the subject being taught and the ability/background of the learners. Park and Gittelman (1992) suggest that natural feedback is likely more beneficial for high ability students, while elaborated feedback is more beneficial for low ability students.

Table 5. Feedback Research Summary (cont.)

Element	Impact on Performance Factors	Impact on Non-Performance Factors	Impact on Learning Efficiency	Comments on Findings
Content - Adaptive	Mory (1992) found no significant difference in post-test performance between students who received adaptive feedback (either KOR, KCR, or various levels of elaborated feedback, based on their response certitude and correctness) and students who receive non-adaptive (elaborated) feedback during instruction.	No studies identified.	In terms of feedback efficiency, adaptive feedback was significantly more efficient than non-adaptive feedback; but in terms of overall lesson efficiency, non-adaptive feedback was more efficient (Mory, 1992)	Adaptive feedback is probably the most applicable form of feedback for ITSs. However, the questions which need answers are: How much adaptability is really necessary for effective learning? And, if adaptive feedback is used, what factors should be used to determine how to adapt it? Response certitude may not be the best clue, because it tends to indicate how much students desire feedback, rather than how much they really need it.
Timing - Immediate	A meta-analysis of studies conducted in realistic learning environments (e.g., classrooms) has found immediate feedback to be more effective than delayed feedback (Kulik & Kulik, 1988). In these studies, treatment and post-test questions are usually different. The more dissimilar the lesson and post-test questions are, the more impact immediate feedback has on performance (Clariana, Ross, & Morrison, 1992).	No studies identified.	No studies identified.	Because studies of immediate feedback tend to be in applied rather than controlled laboratory settings, sometimes they lack rigor (Kulik & Kulik, 1988). However, few seriously doubt that immediate feedback is better than delayed for most instructional circumstances.

Table 5. Feedback Research Summary (cont.)

Element	Impact on Performance Factors	Impact on Non-Performance Factors	Impact on Learning Efficiency	Comments on Findings
Timing - Delayed	Studies conducted in laboratory environments show better performance on tests of retention when feedback is delayed for 24 hours than when it is immediate (e.g., Sturges, 1978; Rankin & Trepper, 1978; Sassenrath, 1975). In these studies, the treatment/lesson and post-test questions are usually either identical or very similar (Clariana, Ross, & Morrison, 1992). Classroom studies have found that teacher wait times of 3-5 seconds result in higher cognitive level learning (Tobin, 1984, 1986, 1987; and Riley, 1986).	No studies identified.	No studies identified.	Findings about the effectiveness of delayed feedback have been well-replicated. However, these studies are generally not representative of typical learning situations; they are more like teaching a test.
Timing - Upon request	Students who could choose whether or not to receive feedback performed significantly better than students who could not choose (Ilgen & Moore, 1987).	Students like being able to choose (Schloss, Wisniewski, & Cartwright, 1988). Hansen (1974) found that subjects allowed control of feedback decreased more in anxiety than subjects not allowed control.	Subjects allowed to choose feedback completed tasks more quickly than subjects who had no choice, with no significant effect on performance (Ilgen & Moore, 1987).	More applied studies need to be done in the area of learner control of feedback. Studies on the effect of learner control with advisement may also be applicable.
Context - With other instructional support available	Effect of feedback is less pronounced when there are other instructional materials (in addition to the questions) available (Clariana, Ross, & Morrison, 1992)	No studies identified.	Students who have instructional support materials available took longer to complete lessons than students who did not (Clariana, Ross, & Morrison, 1992).	Few studies have systematically assessed the impact of this factor relative to feedback, but it is well worth a closer look.

Table 5. Feedback Research Summary (cont.)

Element	Impact on Performance Factors	Impact on Non-Performance Factors	Impact on Learning Efficiency	Comments on Findings
Context - With performance feedback (e.g., scores) available	Students receiving periodic scores based on their practice question performance data performed significantly better than students who did not receive score data (Schloss, Wisniewski, & Cartwright, 1988). Students receiving both quality and quantity (time required) data performed about as well as students receiving quality data alone (Ilgen and Moore). Subjects given feedback comparing their performance to either a class performance curve (Grade Band) or an inferior other person showed larger performance increases than those whose performance was compared to a superior or average other, or who simply received their score without a comparison (Levine & Schneider, 1989). Lewis & Cooney (1987) found that males receiving competitive feedback performed significantly better than females receiving competitive feedback. In addition, females receiving individualistic feedback performed better (but not significantly so) than females receiving competitive feedback.	Levine & Scheider (1989) found that students whose performance was compared to either a Grade Band or an inferior other person were more likely to attribute their performance to effort than students whose performance was compared to a superior or average other, or who received a score without a comparison.	Students receiving both quality and quantity data were more efficient than students receiving quality data alone (Ilgen & Moore, 1987).	Performance feedback is probably most applicable (and has usually been studied) in situations which involve repetitive performance. Where applicable, it seems to be not only effective, but also motivating.
Context - With Personalization	Albertson (1986) found that students who received personalized feedback (i.e., feedback which referred to them by name) performed significantly better than students receiving the same feedback, but not personalized.	No studies identified.	No studies identified.	Needs further study.

Learning Strategies

Definition

Learning strategies (sometimes known as cognitive strategies) are techniques that students themselves use to enhance their understanding and retention of new material. Different strategies are used for different aspects of the learning process or for different learning situations. Strategies for *elaboration*, for example, help students to establish links between the information to be learned and what they already know, thereby enhancing recall. Strategies for *comprehension monitoring* enable students to recognize when they do not understand something.

Purpose

The purpose of including learning strategies in instruction is to enable students to become independent, effective learners. Some students have their own learning strategies, and would not benefit greatly from learning strategies instruction. Others, however, require more explicit guidance.

Summary and Evaluation of Research

Learning strategies research can be divided into two categories: 1) studies which identify the types of strategies used by effective learners; 2) studies which examine factors which can affect the use of learning strategies; and 3) studies which evaluate the effectiveness of various learning strategy training programs.

Strategy Identification Studies

Strategy identification studies identify the types of learning strategies used by effective learners. Generally, these types of studies involve comparisons of older or more successful learners with younger or less successful learners. The comparisons in Table 6 are based on a review of the literature by E. Gagne (1985).

Table 6. Comparison of Learning Strategy Use by Learner.

More Effective Learners	Less Effective Learners
Have strategies for differentiating between more and less important information, and will selectively attend to important information.	Are unable to differentiate between ideas of varying importance.
Have strategies for remembering new information.	Lack strategies for remembering new information
Use strategies for organizing information (e.g., clustering related items, summarizing)	Do not organize information
Monitor their own learning	Do not monitor their own learning, or do not monitor it effectively.

Gagne also points out that effective learners not only have a wide repertoire of learning strategies, but also know *when to use which ones*. Very effective learners will constantly monitor their level of understanding and may change strategies accordingly.

A variety of different nomenclatures exist for classifying the different types of learning strategies. One of the most comprehensive is by Weinstein and Mayer (1986), which lists eight categories. These categories, their descriptions, and example tasks to which they could be applied are listed in Table 7.

Table 7. Types of Learning Strategies.

Learning Strategy	Description	Application
Basic rehearsal strategies	Actively reciting or naming presented items during learning	Memorizing lists of items such as names of presidents or state capitals
Complex rehearsal strategies	Reading material aloud, copying material, taking verbatim notes, underlining	Memorizing material from a text passage
Basic elaboration strategies	Building internal associations between two or more items to be learned	Memorizing foreign language vocabulary
Complex elaboration strategies	Integrating new information with information already known	Paraphrasing, summarizing, developing analogies from new material
Basic organizational strategies	Clustering items into groups to remember them	Memorizing items from a list.
Complex organizational strategies	Developing outlines, concept maps, networks	Identifying main ideas and supporting concepts in a passage
Comprehension monitoring strategies	Establishing learning goals, assessing degree to which goals are being met, and modifying strategies as needed to meet goals.	Selective attention during reading
Affective and motivational strategies	Changing thought patterns	Reducing test anxiety, maintaining motivation, maintaining concentration, focusing attention

Factors Affecting Use of Learning Strategies

Most people probably use learning strategies to some extent. There are several factors which seem to be related to the degree to which individuals use learning strategies effectively.

These include: level of domain knowledge, use of cognitive monitoring, persistence in the use of less effective strategies, learning context, self-efficacy, level of intrinsic motivation, and lack of training or experience. These factors are summarized in Table 8.

Effectiveness of Learning Strategy Training

As stated in the previous section, training in learning strategy use does help students to use these strategies more often. This does not necessarily result in an improvement in academic performance, however. Factors which may influence the impact of learning strategies training on academic performance include:

Learner ability. There is some evidence which suggests that learning strategies training may actually hinder higher ability students in some cases (Brown, Trathen, & Dole, 1992). Perhaps these students already have effective strategies of their own, and being instructed to use some other approach confuses them. However, this does not necessarily mean that high ability students would not benefit from learning strategies training--just that it may need to be presented differently.

Lack of domain knowledge. Knowledge of learning strategies may make students better learners, but it is clearly no substitute for domain knowledge (Weinstein & Mayer, 1986). Solving a problem requires both domain knowledge and general cognitive strategies (Kelley, 1992).

Applicability of learning strategies training to particular academic situations. It is not enough just to teach about learning strategies. Sometimes it is necessary to teach the right learning strategy at just the time it is needed, and to point out why it is an appropriate strategy to use. Younger or low ability learners, for example, require complete, explicit instruction that is situated in the context of the domain being studied (Campione, 1987; Loper & Murphy, 1985; Paris, Cross, & Lipson, 1984; Pressley, 1986).

As long as learning strategies instruction is carefully targeted, there is reason to believe that it can have a positive impact on academic performance (Loper & Murphy, 1985; Miller, 1985).

In summary, the research on learning strategies use clearly demonstrates that learning strategies instruction can be very beneficial. It also lets us know the conditions under which learning strategies are most likely to be used, and factors which may influence their effectiveness. However, more research which explores the interactions between the various factors would help intelligent tutoring systems to better target learning strategies instruction to the needs of individual learners. In addition, research is needed which answers the questions such as how often should learners be exposed to learning strategies concepts, and to what extent these strategies be incorporated into domain instruction (as opposed to being taught separately).

Table 8. Factors Affecting the Use of Learning Strategies.

Potential Factor	Definition	Effect on Learning Strategy Use
Level of domain knowledge	Student's knowledge of domain to which the learning strategy is to be applied	Students' degree of domain knowledge appears to have some effect on the types of strategies used (Gagne, 1985; Garner, 1990).
Use of cognitive monitoring	Student's tendency to assess his or her level of comprehension	If students do not realize when they do not understand, they will not know that they need to apply a learning strategy (Garner, 1990; E. Gagne, 1985).
Persistence in the use of less effective strategies	Sub-optimal learning strategies, such copying text verbatim rather than paraphrasing or summarizing	If less effective strategies work (albeit less efficiently), student may tend not to use more effective ones (Garner, 1990).
Learning context	Learning situation -e.g., classroom environment, domain being studied	Students tend to use more effective learning strategies in classrooms which emphasize a mastery learning approach (Ames and Archer, 1988). Also some evidence suggests that students may use different learning strategies for different subjects (Young, Arbreton, & Midgley, 1992).
Self-efficacy	Assessments of one's own ability to perform in novel or difficult situations.	High perceptions of self-efficacy are consistently correlated with greater and more efficient strategy use (Bouffard-Bouchard, 1990; Pintrich & De Groot, 1990; Bandura, 1989).
Level of intrinsic interest in domain being studied	The extent to which the student is motivated to learn the subject for its own sake	Intrinsic interest is correlated with strategy use (Pintrich & De Groot, 1990).
Training and/or experience in cognitive strategy use	The extent to which the student has been taught to use and practiced using cognitive strategies	Training helps students to use strategies more (Weinstein & Mayer, 1986; Dansereau et al., 1975).

Applicability to ITS Development

It is clearly desirable for an intelligent tutoring system to be able to offer learning strategies instruction to students. However, there are several practical issues which need to be addressed before it can be implemented.

First, taking time out for learning strategies instruction will cause some students to progress through the curriculum more slowly than others--at least initially. This is not necessarily a bad thing, especially if the students are really learning. However, within the context of a typical school environment where all students spend the same amount of time in the classroom, listen to lectures together, and take tests together, individualized instruction could be a management headache. Either supplementary instruction needs to be partitioned out in some way (e.g., so slower learners could receive learning strategies instruction after school, or during study periods), or the structure of a typical school day needs to be radically changed.

Second, it may be difficult to target learning strategies instruction to individual learners. First the system must obtain the data it needs to decide whether or not such instruction is necessary. Then, if learning strategies instruction is best integrated with domain instruction, it will be necessary to figure out how to get the ITS to reorganize learning strategies information to adapt to particular situations.

Summary

This chapter has presented findings about specific teaching behaviors that could be implemented in intelligent tutoring systems. The next logical step is to integrate these behaviors into a single approach to effective instruction, and to represent it in a more computer-friendly form.

III. SELECTION OF AN INSTRUCTIONAL APPROACH

The purpose of this step was to select an instructional approach for initial implementation within an intelligent tutoring system. This chapter reviews some of the more influential instructional approaches including direct instruction, discovery learning, mastery learning, and cognitive apprenticeship.

Before proceeding, we must identify what we mean by instructional approach. An instructional approach is:

> *a theoretically guided set of instructional prescriptions or actions which facilitates the transfer of information from teacher to student.*

This working definition was selected because it illustrates an important characteristic of the instructional approach; namely, approaches have two distinct, but related components. The

theoretically guided portion of the definition identifies the first component. It refers to the set of assumptions made about the nature of teaching and learning. The *set of instructional prescriptions or actions* portion of the definition identifies the second component. It refers to the actual classroom activities which are required to instantiate the underlying assumptions. Simply, assumptions made about the nature of teaching and learning determine what activities are legitimate within a given approach.

Suppose that we assume learning occurs passively. That is, we believe individuals learn by merely absorbing information from their environment. Acceptance of this theory implies certain things. For example, telling students target content should be sufficient to insure learning. *Lecturing*, then, is a valid teaching action derived from the assumption that learning is a passive phenomena. Obviously, other teaching actions that involve telling students information (e. g., *give students a summary)* are equally valid. The set of valid activities, taken together, comprise the activity structure of the approach. The activity structure is essentially the set of observable activities associated with a particular approach. Therefore, when most people speak of instructional approaches, they are referring to the activity structure or the observable characteristics of the approach. The assumptions which underlie these activities, however, are equally important. As we shall see, faulty assumptions can lead to faulty instruction.

Two problems complicate the task of defining the term instructional approach. First, most teachers do not adhere to a single approach; rather, they build eclectic models of instruction based upon their own experiences in the classroom. This is not necessarily a problem for us, however, because we are not dealing with classroom instruction. We are concerned with intelligent computer-based instruction. Second, differences between instructional approaches are often subtle and elusive. We address the second problem. Eventually, we will select an instructional approach suitable for intelligent tutoring system implementation.

The overall goal of the Effective Teaching Behaviors project is to define and describe sets of effective teaching behaviors for intelligent tutoring systems. The instructional approach provides an ideal starting point because it essentially acts as a *container* which can be filled with effective teaching actions. By the container analogy, we mean to imply that instructional approaches have two properties. First, they have some general and unmalleable characteristics like *teacher-direction of instruction*. These characteristics define the approach and are analogous to the shape of the container. Second, there are many specific characteristics such as *provide an advance organizer* which are independent of instructional approaches. Many of these characteristics were identified in the first phase of this project. They are interchangeable in that we can add them in varying amounts to almost any approach. Therefore, they are analogous to the content of the container. Presently, we intend to select the best container for the effective teachi behaviors identified in the first phase of this project. In succeeding tasks, we will systematically integrate the effective teaching behaviors identified in the first phase of the project with the approach identified during this phase. Ultimately, the container and its contents will be used to devise a template of effective teaching behaviors suitable for implementation as the pedagogical component of intelligent tutoring systems.

Examination of Specific Instructional Approaches

Generally, there are four classes of approaches: 1) those based on objective and reception theories of learning (e.g., Ausubel, 1977; Rosenshine, 1979; Peterson, 1979), 2) those based on inquiry theories of learning (e.g., Hermann, 1969; Nuthall & Snook, 1973), 3) those based on egalitarian and Socratic theories of learning (e.g., Bloom, 1984; Slavin, 1987), and finally, 4) those based on cognitive and constructivistic doctrines (e.g., Palincsar & Brown, 1984; Collins, 1988; CTGV, 1992). Direct instruction, discovery learning, mastery learning, and cognitive apprenticeship fit these classes, respectively. Table 9 depicts some of the key similarities and differences which will be discussed in depth throughout the remainder of this document.

Table 9. Comparison of Direct Instruction, Cognitive Apprenticeship, and Discovery Learning.

Variable	Direct Instruction	Cognitive Apprenticeship	Discovery Learning
Theory of learning implied by approach	reception learning	constructivism	inquiry, experiential, (constructivism)
Mode(s) of information exchange	telling of content	telling, showing, doing	doing
Nature of the learning	passive	active, collaborative, experiential	active, experiential
Role of the instructor	benevolent despot	master, coach	guide
Role of the student	sponge	apprentice	explorer
Dominant teacher activities	lecturing, questioning and testing students	modeling, coaching	observing student progress
Dominant student responses	listening, answering questions, completing homework	watching, listening, doing, reflecting, articulating, exploring	exploring
Source(s) of feedback	mostly from teacher	teacher, task, self	mostly from the task
Control of pace of lesson	teacher	shared	student
Control of lesson content	teacher	teacher to shared	student
Degree of individualization	teacher-centered, little individualization	collaborative, highly individualized	student-centered, highly individualized

For each approach we will:

- discuss underlying assumptions
- discuss what these assumptions entail in terms of instructional activities
- identify important findings from the professional literature
- discuss implications for the use in intelligent tutoring

Direct Instruction

Direct instruction is perhaps the most common instructional approach. It is not an exaggeration to say that all American students have, at one time or another, been exposed to direct instruction.

Assumptions

Direct instruction is guided by a reception theory of learning. Ausubel states that, "in reception learning the principal content of what is to be learned is presented to the learner in more or less final form" (Ausubel, 1977). "More or less final form" means that the learner does not have to alter the information in order to use it. Therefore, telling students the target content is sufficient to insure learning.

Activity Structure

Rosenshine has perhaps provided the best description of direct instruction (1979). He identifies the following attributes:

- all activities are teacher-directed and monitored
- a strong academic focus is maintained
- content is highly structured and thoughtfully sequenced
- goals are clearly and explicitly stated
- the time allocated for instruction is sufficient and continuous
- the coverage of content is extensive
- the teacher structures student/teacher interactions
- questions are at a low cognitive level to insure high rates of success (approximately 70%)
- feedback is immediate and academically-oriented

Thus, in direct instruction, the teacher controls all facets of the instructional process including the instructional objectives, content, pace, the quality and quantity of student/teacher interactions, evaluation, and feedback. The primary mode of instruction is the lecture, although supplemental media like movies, film, textbooks, and workbooks are also acceptable. Some researchers claim that up to 85% of the time in direct instruction is spent in lecture (Davis, 1983).

Research

Many direct instruction-related research studies have focused on the types of activities which positively correlate with achievement. Brophy recognizes the following positive correlates of academic achievement (1986):

- content covered
- time allocated
- academic-engaged time
- clear, well-structured presentation of information
- high rates of student success
- regular and extensive feedback

Rosenshine identifies *extensive content coverage* as an important characteristic of direct instruction (1979). Content coverage is roughly synonymous with the opportunity to learn; therefore, the importance of this variable is obvious. Simply, individuals with more opportunity to learn will tend to learn more. Measures of academic-engaged time, usually counts of on-task behavior, are often used as to indicate the amount of content covered. For example, the number of minutes per hour that a student is observed reading is a suitable measure of content coverage. The relationship between content covered and scholastic achievement is often assessed by means of correlations between counts of on-task behavior and achievement measures. Bloom (1976), for example, found correlations ranging from .40 to .52 between measures of student attention and scholastic achievement. Stallings and Kaskowitz (1974) found a similar range of correlations between various measures of content covered and achievement.

Effective teacher management of the classroom is frequently cited as a correlate of achievement. Rosenshine, for example, claims that teacher-directed classrooms are more successful than non-teacher-directed classrooms (1979). A separate line of educational research, that of learner control, lends credibility to this claim. Specifically, researchers have discovered that too much learner control of instructional events is detrimental to learning for certain types of information and student populations. Two explanations are advanced. First, learners with too much control of instruction often either opt themselves out of instruction entirely or they choose the path of "least resistance." Secondly, some learners may be ill-equipped to deal with the cognitive demands of simultaneously sequencing instructional events and learning novel material (Carrier, 1984; Steinberg, 1989).

Other variables characteristic of direct instruction, such as *low-level questions*, *controlled practice*, and *immediate and academically-oriented feedback* are also associated with increases in achievement (Rosenshine, 1979). Rosenshine suggests that the activity structure of direct instruction promotes achievement relative to *open* or discovery-oriented approaches. Open approaches are antithetical to direct approaches, in that they are student-directed, rather than teacher-directed. Peterson confirmed Rosenshine's conclusion in a meta-analysis comparing direct and open approaches (1979). She found effect sizes which favored direct instruction for a variety of achievement outcomes. Effect sizes ranged from -.78 to .41 across several achievement measures (negative effect sizes favor direct instruction). The observed variability of effect sizes suggests two possibilities. First, direct instruction differentially affects various achievement

measures. That is, the effects of direct instruction are dependent on the measures selected. Second, some combination of statistical, experimental, and measurement errors inflated the variability of effect sizes. Despite the somewhat conflicting results, direct instruction seems to promote a variety of achievement outcomes.

Peterson compared direct and open approaches in terms of affective outcomes (1979). The results were somewhat mixed, but open approaches seemed to slightly promote outcomes like positive self-concept, school-attitudes and attitudes toward teacher slightly more. Further, open approaches reduced anxiety and increased independence.

Student characteristics seem to affect the relationships between direct or open instruction and achievement. For example, Peterson cited a study by Ward & Barcher in which low ability students performed equally well under direct and open approaches, but high ability students performed better under direct instruction (Peterson, 1979). This finding is in line with Ausubel's claim that learners must reach some developmental milestone before they are capable of reaping the benefits of reception learning (Ausubel, 1977). Ausubel's conclusion is controversial, however. Grapko (1972), for example, found that the achievement of high ability students did not differ between direct and open instruction, but that low ability students performed better under direct instruction. While it is clear that student characteristics moderate the effectiveness of instructional approaches, it is not clear how.

Implications for Intelligent Tutoring Systems

Generally, direct instruction can be attacked on two points:

- it encourages passivity which can lead to non-meaningful learning
- achievement is not the only important educational outcome

Reception learning is passive. Learners are assumed to be like *sponges* absorbing information from their environment (Schank & Jona, 1991). However, this assumption could be dangerous (Linn & Clancy, 1990). Passive learning facilitates idiosyncratic learning--i.e., what is learned is mediated by what the learner already knows or believes. Large student groups, minimal student choice, and highly structured and limited student/teacher interactions create a situation in which student misconceptions can go undiagnosed. In addition, direct instruction encourages the learner to take what the teacher says as absolute fact because of the apparent omnipotence of the instructor. Rote memorization is encouraged and *multiple perspectives* or diverse viewpoints are discouraged (Schank & Jona, 1991). The result of this assumption is that learners often adopt expeditious, but ineffective, solution strategies which give the appearance of understanding but are actually based on some superficial aspect of the problem. Therefore, telling is not sufficient to insure learning. Simply put, learners often do not know enough about their own cognition to optimize learning (Winne, 1989). Telling does not insure that the student will attend to, assimilate, or store the information properly.

Second, achievement is not the only desirable outcome of instruction (Peterson, 1979). Other outcomes, such as positive school attitudes and self-concept are also important. Unfortunately, advocates of direct instruction often base their arguments on the observed

achievement gains associated with its use. The instructional process should maximize as many positive outcomes as possible; direct instruction does not.

These arguments do not mean that direct instruction cannot be an effective means of transmitting information; it is. Rather, direct instruction may not always be the *most* effective means of instruction. Direct instruction is probably too limited for intelligent tutoring because it relies too heavily on only one mode of instruction: telling content. Intelligent tutoring systems afford educators with the means to instantiate much richer instructional approaches than direct instruction.

Discovery Learning

The discovery learning approach is largely student directed. In this sense, it is the theoretical opposite of direct instruction. In fact, the *pure* forms of direct instruction and discovery learning are viewed as opposite poles of the instructional continuum (Hermann, 1969). Instructional approaches probably do not exist in a pure form, however. Rather, they are mixed together, diluted, and altered. This is certainly true of discovery learning. Discovery is almost always tempered with some degree of guidance in practice. Generally, the diluted or mixed approach is called guided discovery. The following table offers a comparison of discovery learning and direct instruction.

Table 10. Comparison of Discovery Learning and Direct Instruction.

Discovery Learning	Direct Instruction
Students enjoy maximal control of content, pace, and sequence of instructional events.	Students have few instructional choices.
Student/teacher interactions are unstructured and infrequent.	Interactions are highly structured and frequent.
Feedback is infrequent. It is likely to come from task performance, not the teacher.	Feedback is more frequent and usually originates with the instructor.
Materials are not necessarily structured.	Materials are structured.
High-level, open-ended questions are used.	Low-level questions are used more frequently.
Educational objectives are not necessarily clear.	Objectives are explicit and clear.

Assumptions

Discovery approaches are founded on an inquiry theory of learning. Proponents of inquiry-based learning assert that learners find the process of discovery intrinsically challenging and rewarding; hence, outcomes like motivation, creativity, independence, and meaningful learning are facilitated (Nuthall & Snook, 1973; Peterson, 1979).

Bruner (1961) claims that discovery learning is " a matter of rearranging or transforming evidence in such a way that one is enabled to go beyond the evidence so reassembled to additional new insights". Therefore, it seems clear that the implicit objective of discovery learning is to place students in an inquiry mode which requires the use of inductive processes.

Activity Structure

The activity structure of the discovery approach is ambiguous because of the complex nature of inquiry and the pervasive disagreement about how to operationalize discovery. One definition, for example, says that the discovery learning approach is two-staged. In the first stage, students are asked to solve problems or discuss relevant examples from experience. In the second stage, the problem and/or example is altered. The student must concomitantly alter the solution algorithm or strategy in order to successfully cope with the problem. During this stage, the student discovers new principles or methods which facilitate navigation of the problem space (Nuthall & Snook, 1973).

This is only one conceptualization of the discovery approach, however. Davis (1983) claims that discovery learning is really a process which involves a sequence of four steps. First, the learner must sense a problem or discrepancy in some set of knowledge. Presumably, in a guided version of discovery learning, the teacher would create the problem or discrepancy. Second, the learner must define the problem and formulate a solution plan. Next, the learner must search for relevant information, hypothesize about the problem, and occasionally backtrack to previous parts of the sequence. Finally, the learner must resolve the problem or eliminate the feelings of "disequilibrium."

Defining the activity structure of discovery learning is a difficult task because of the disagreement among discovery learning proponents. It has been suggested that the only common theme present in the assortment of definitions of the discovery approach is that it is not "telling" (Nuthall & Snook, 1973). The role of the student is clear. He or she must work through some problem inductively arriving at some new concept, principle, or theory. The role of teacher, however, is less clear.

Based upon these various definitions, we suggest that the role of the teacher in guided discovery is: 1) to provide some initial problem or topic of inquiry and 2) to provide feedback when necessary. All other phases of the instructional process seem to be the responsibility of the student.

Research

Hermann (1969) offers the following summary of discovery learning findings:

- Rule-example learning (a technique often used in direct instruction) promotes retention relative to discovery. In rule-example learning, a rule is presented followed by a specific examples.

- Discovery approaches promote transfer relative to direct instruction. That is, a student who has discovered some principle, concept, or theory on his own is more able to apply it some other domain of knowledge.

- As the difficulty of the transfer task increases, the efficacy of discovery learning also increases. In other words, the more dissimilar the transfer task is from the learned task, the more effective discovery learning becomes.

- Discovery learning may be more effective when the learner's subject knowledge is limited. This suggests that novices should be taught with discovery methods although Husic, Linn, & Sloane (1989) suggest otherwise.

- Discovery learning is more effective when the material is academic.

- The discovery method is more effective with low ability than with high ability populations.

- After material has been learned by discovery, immediate verbalization or further learning adversely affects the original learning. Therefore, it is probably not a good idea to give learners a summary or post-organizer following discovery learning.

- A "reasonable" degree of guidance is better than no guidance. Hermann does not explain what he means by a "reasonable" degree of guidance, but logically some instruction and feedback will improve performance.

In an interesting study, Husic, Linn, & Sloane (1989) found that teachers with introductory programming classes tended to use direct instruction while teachers with advanced classes were more likely to use discovery methods. These choices seemed to be warranted on the basis of achievement. There were significant positive correlations between instructional approach and student performance. For example, in the introductory classes "identifies important information" correlated .71 with achievement while "encourages independent inquiry" correlated .50 with achievement in the advanced classes. As expected, "encourages independent inquiry" correlated -.70 with achievement in the introductory classes.

As mentioned in the previous section, Peterson found that open or discovery approaches slightly facilitated some affective outcomes like positive attitude, self-concept, independence, and creativity (Peterson, 1979). Hermann reported that discovery methods promoted transfer (1969)

and Husic et al. found that discovery learning was effective for advanced students. Thus, some of the claims of discovery learning proponents are supported.

Implications for Intelligent Tutoring Systems

Although discovery learning methods have a place in instruction, several factors make total reliance on discovery impractical, if not unfeasible. First, conceptual definitions of discovery learning are ambiguous. Therefore, it is difficult to accurately instantiate the true meaning of discovery. Second, discovery learning is inefficient because the amount of content covered relative to time expended is low. Learners spend a lot of time while covering only small amounts of material. Third, the nature of discovery insures higher rates of student failure and the possibility of concomitant decreases in motivation, attitudes, and self-concept. Finally, discovery learning promotes a disparity between the cognitive experiences of the teacher and student. Therefore, it is difficult for the teacher to provide adequate feedback (Nuthall & Snook, 1973).

We suggest that discovery techniques do not provide adequate or complete instructional capabilities for intelligent tutoring because of vague instructional characteristics, inefficiency of learning in terms of amount of material covered relative to time invested, and problems associated with the lack of guidance. Discovery can be extremely useful as an instructional supplement, but it does not provide the ITS developer a full palette of options.

Mastery Learning

Mastery learning approaches emphasize student mastery of content, not the amount of content covered. There are several mastery variants which, at first glance, appear to be entirely different instructional approaches. They do, however, share a common philosophy.

Assumptions

Mastery learning approaches are guided by an egalitarian philosophy of education. That is, all individuals are given equal opportunity to excel in an individualized environment. This is accomplished by holding student achievement constant while time is allowed to vary. Normally, significant positive correlations are observed between intelligence and scholastic achievement. Thus, individuals with lower intelligence are placed at a disadvantage. Mastery learning approaches circumvent this problem by giving all students enough time to master the content (Keim-Abbott & Abbott, 1977).

Activity Structure

In traditional classroom-based learning, there is a finite time frame imposed on upon each lesson. Generally, students are tested at the end of the each lesson. This means that all students have the same amount of time to learn the material. If students have not mastered the content by the time of the test, they do not get another chance. In contrast, mastery learning holds achievement, not time, constant. Students must meet or exceed some mastery criterion in order to proceed, regardless of the time required. This allows more students the opportunity to master the content.

There are at least two instantiations of mastery learning: the Keller Personalized System of Instruction and Bloom's mastery learning approach. The Keller Personalized System of Instruction is essentially a discovery-oriented mastery approach. Students are given a study guide which they use to guide themselves through a lesson. Students can attend a regularly scheduled class, work on their own, or simply take the test without studying the material. Occasionally, the instructor lectures students on important issues or concepts. Students must pass a test in order to proceed to the next lesson. If a student fails the test, there is no penalty, but they must retake the test. (Kulik, Kulik, & Cohen, 1979).

Bloom's mastery learning is somewhat like direct instruction. The key difference lies in the fact that Bloom's system provides for individualization of instruction. In Bloom's (1984) system:

> *Students learn the subject matter in a class with about 30 students per teacher. The instruction is the same as in the conventional class... Formative tests...are given for feedback followed by corrective procedures and parallel formative tests to determine the extent to which the students have mastered the subject matter.*

Bloom's notion of mastery learning capitalizes on some of the correlates of academic achievement (e.g., *academic focus, use of teacher-directed and monitored activities)* mentioned previously.

Whatever the form, the key features of mastery learning are:

- A mastery criterion. The teacher sets a minimum level of success which must be met.
- Small segments of content. Instruction is divided into small segments.
- Student control of pace. The student is allowed as much time as necessary to complete a lesson.
- Frequent assessment. Tests follow each lesson. They determine whether the student moves to next lesson or receives remediation.
- A system of corrective feedback and remediation which capitalizes on the benefits of individualized instruction. Feedback and remediation are tailored to individual needs of each student. If a student is successful in one area and unsuccessful in another, he or she receives help only in the problem area.

Research

Bloom's 1984 paper identifies the *two-sigma problem*. Essentially, the 2-sigma problem refers to the fact that one-on-one tutoring results in achievement gains of two standard deviations over conventional methods of instruction. Thus, the *problem* is how to attain these levels of achievement without using one-on-one tutoring. According to Bloom, mastery learning provides the best answer because of the *individualized* nature of the instruction.

Bloom (1984) claims that mastery learning allows 80% of the students to attain a level typically reached by only 20% under traditional methods. Therefore, more students have the opportunity to excel. A meta-analysis by Slavin (1987) reported smaller effect sizes than those

found by Bloom; nonetheless, they also favored mastery learning. However, Slavin noted that when time was controlled, positive effect sizes nearly disappeared. Additionally, Slavin found that the achievement gains produced by mastery learning were strongly moderated by the type of test used. Experimenter-made tests showed larger effect sizes than standardized achievement tests.

A meta-analysis of Keller's Personalized System of Instruction (PSI) also showed positive effect sizes (Kulik, Kulik, & Cohen, 1979). Analysis of variance revealed that Keller's PSI is equally effective for high and low ability students. Additionally, Keller's PSI seemed to be more effective in certain domains, such as the social sciences; and essay test performance was enhanced relative to objective test performance. Mastery learning approaches seem to enhance student achievement and have obvious implications for self-concept, motivation, and school attitudes.

Implications for Intelligent Tutoring Systems

The literature clearly indicates that mastery learning improves achievement over conventional methods because of the individualized nature of instruction (Bloom, 1984). There are several problems, however. First, the facilitative effects of mastery learning tend to diminish or disappear when the effects of time are controlled as is demonstrated by Slavin (1987). Many mastery learning studies do not control for the effects of time. Control group subjects get only *X* amount of time while mastery learning subjects receive all the time they need to master the content. It is no wonder that they achieve at higher levels. Second, a decision must be made about what to do with learners who finish before their classmates. Should they go on, wait for their classmates to catch up, or review the same material in more detail? Finally, some attribute the positive effect sizes favoring mastery learning to the fact that teachers key on testable concepts. Slavin's study showed that this is probably true. These issues indirectly affect the decision to use mastery learning approaches in intelligent tutoring. If, for example, the achievement gains associated with mastery learning are the result of time effects, then we may be less eager to use the approach in intelligent tutoring.

The mastery learning philosophy and its implications for individualized instruction are ideally suited to intelligent tutoring systems. The computer allows each student to progress at his or her own pace without raising the problem of what to do with quick-finishers. We suggest applying the mastery learning philosophy to intelligent tutoring system design because it is fairer to lower ability students, it allows more students to master the material, and it facilitates more individualized instruction. In fact, many intelligent tutoring projects already utilize the notion of mastery.

Cognitive Apprenticeship

Cognitive apprenticeship is an approach characterized by the *showing, telling, and doing* of authentic tasks in authentic contexts. It is designed to reduce the problem of *inert* or useless knowledge. The fundamental goal of education is to develop and foster sets of working knowledge and strategies which can be applied to real world problems. Unfortunately, all too often the more immediate goal of short-term retention or cramming predominates. As a result, students seem unable to apply facts or concepts learned within an academic setting to problems outside of that setting. Cognitive apprenticeship was designed to promote transfer of knowledge

to real world settings, by eliminating the artificial separation of knowing and doing that characterizes conventional instructional methods (Brown, Collins & Duguid, 1989; Collins, 1988).

Assumptions

Cognitive apprenticeship derives from several ideas about the nature of cognition, most notably, constructivism. Merrill (1991) identifies the following tenets of constructivism:

- Learning is constructed from experience.
- There is no shared reality.
- Learning is an active process.
- Learning is collaborative--that is, meaning is derived from multiple perspectives.
- Learning is situated.
- Testing should be an integral component of the learning task.

In the following section, we will examine the tenets of constructivism in detail. This does not mean that advocates of cognitive apprenticeship are pure Contructivists; however, many of the assumptions of constructivism are intricately tied to the activity structure of cognitive apprenticeship.

The notion that *knowledge is constructed from experience* implies that education should be experiential. This assumption directly contradicts *objectivism.* Objectivists are opposed to the idea that knowledge is constructed from experiences with the world. Experience, they say, does not play a role in the structuring of knowledge because the properties, entities, and relations in the world are already completely and correctly structured (Duffy & Jonassen, 1991). Traditional methods of instruction such as direct instruction are closely aligned with objectivism. Proponents of cognitive apprenticeship, on the other hand, believe that knowledge is constructed from experience. However, this belief does not preclude telling students information. Rather, cognitive apprenticeship allows for both experiential learning *and* telling.

The second assumption, that *there is no shared reality,* is more controversial. On one level, this assertion is quite true. That is, no two people in the world share exactly the same experiences. Therefore, it seems reasonable to conclude that each individual has deeply personal perceptions of what reality is and isn't. On another level, however, this assumption is totally absurd. Obviously, the majority of our knowledge of the world is not idiosyncratic but shared (Merrill, 1991). Some knowledge, in fact, must be common to all people. For example, in our culture we all know that red means stop and green means go. What would happen if everyone had their own idea of the meaning of a stoplight? Without question, operating a motor vehicle would become inordinately dangerous. However, although this assumption is wrong in strictest sense, the main point of the Constructivists is that people do not always see things in the same way.

The third assumption, that *learning is an active process,* is generally supported by the cognitive literature. We do not merely *absorb* information; rather, we *construct* it, based upon what we already know and believe (Linn & Clancy, 1990; Schank & Jona, 1991; Smith, 1988).

Thus, it seems only natural to use instructional approaches which capitalize on our constructive tendencies.

The fourth assumption, that *learning is a collaborative process*, stands in opposition to direct instruction. Collaboration and multiple perspectives are important educational tools. In direct instruction, there is only one authority, the instructor, and usually only one viewpoint. Proponents of constructivism, on the other hand, hold that meaningful learning occurs when learners examine multiple perspectives. Collaboration with others encourages the examination of multiple perspectives, which in turn serves to flesh out knowledge and promote social goals. As was observed in the discussion about direct instruction, exposure to relevant academic stimuli is positively correlated with achievement. Exposure to multiple perspectives simply represents exposure to more complex and diverse academic stimuli. It follows, then, that collaboration and multiple perspectives should improve the quality of information available to the student.

The fifth assumption, that *learning is situated*, is quite important. The implication is that all learning should occur in the context or sphere of its use in the real world (Collins, 1988; Wilson & Cole, 1992). Traditional instruction ignores this maxim. Learning in conventional classrooms separates knowledge from its uses in the real world. Students learning to solve algebra word problems, for example, are often given unrealistic and uninteresting examples, which serve purely pedagogical purposes. Students come to associate algebra with academic settings and irrelevant word problems. As a result, they fail to see the practical uses of algebra. It should be noted, however, that other researchers claim that the notion of situated cognition is extreme (Sandberg & Wielinga, 1992). Meaningful learning can occur in the absence of strict situation. Additionally, sometimes situated cognition can lead to solution strategies which are situation-specific. Nonetheless, the preponderance of the evidence suggests that situated learning results in the development of effective solution strategies (Clancey, 1992). Authentic learning tasks capitalize on the benefits of situated cognition. Learners discover solution strategies in the context of their use. This serves to structure knowledge relative to its use in the real world. Therefore, situated learning reduces the problem of inert knowledge (Collins, 1988).

The final assumption of constructivism states that *tests of learning should be integrated with the learning task itself*. This means that demonstrations of competence should occur as a by-product of the interaction of the learner with real tasks and materials during the learning process. Traditionally, tests are separated from the rest of the instructional process. This is a dangerous situation, in the contructivist view, because it further serves to remove knowledge from the sphere of its use.

Activity Structure

Cognitive apprenticeship is characterized by the showing, telling, and doing of authentic tasks in authentic contexts. It represents a return to the resource-intensive mode of instruction characteristic of the traditional trade apprenticeships. In terms of the variety of activities it calls for, it is the richest of the instructional approaches reviewed so far. The following sections will describe the activity structure of cognitive apprenticeship in greater detail.

Content. Generally, four types of knowledge are taught in cognitive apprenticeship: 1)

domain knowledge, including conceptual, factual, and procedural information; 2) heuristic strategies or "tricks of the trade"; 3) control strategies; and 4) learning strategies (Collins, Brown, & Newman, 1989; Collins, 1988; Wilson & Cole, 1992). In contrast, conventional methods only attend to domain knowledge. Strategy instruction is wholly ignored despite the fact that many researchers have shown that cognitive strategy instruction facilitates student achievement (e.g., Palincsar & Brown, 1984). Simply, students must be instructed in tacit, heuristic knowledge as well as textbook knowledge (Collins, 1988).

Sequence. Content should be sequenced from *simple to complex, with increasing diversity of information*, and from *global to local skills* (Wilson & Cole, 1992). Simple to complex sequencing means teaching easier, lower-level material before harder, higher-level material. Increasing diversity of material means that as the lesson progresses, more examples and practice contexts are employed. Finally, the global/local skills distinction means that it is the teacher's job to help the students acquire a general mental model of the problem early in the instruction. Only later does the teacher instruct specific skills. For example, suppose that we are teaching students to add. First, we would teach students single-digit addition. We would be certain to emphasize uses for addition skills in the real world. Gradually, we would begin to include multiple-digit problems. We would begin to provide examples of how to apply addition knowledge to specific tasks like word problems. Ultimately, we would provide students with situated learning environments like running a imaginary store or keeping records for a imaginary bank.

Nature of the learning task. Content must be taught or situated in the context or sphere of its use to avoid the problem of inert knowledge (Collins, 1988; Lajoie & Lesgold, 1989; Wilson & Cole, 1992). Knowledge is traditionally taught in abstract ways which promote the use of superficial and largely ineffective strategies; that is, strategies which facilitate short-term retention of material at a highly superficial level (Wilson & Cole, 1992). Students, for example, may merely key in on some superficial aspect of a word problem which allows them to answer the question correctly without fully understanding the concepts involved.

Collins suggests the use of multiple contexts in instruction because they foster both general and specific knowledge (1988). Multiple contexts refer to different scenarios which require the use of the same skill. The use of authentic, multiple contexts provides the learner with specific examples of how knowledge is used in the real world. Providing several examples allows the student to generalize across those examples and contexts. Thus, knowledge becomes both specific and general.

Supposedly, situated learning has the following benefits: 1) students learn the conditions for applying the knowledge, 2) invention is fostered, 3) students see the implications of the knowledge, and 4) authentic contexts structure knowledge relative to the sphere of its use (Collins, 1988). In short, situated learning reduces inert knowledge.

Instruction. As mentioned, cognitive apprenticeship has showing, telling, and doing activity structures. The teacher shows the student how something works or how to do something, tells why it is that way, and then the student does it.

Generally, some process or action is modeled. The teacher shows how the process or

action unfolds and simultaneously tells the reasons why it happens that way. It is important that the teacher model and explain, or show and tell, *simultaneously* because the student needs access to explanations as he or she observes the details (Collins, 1988; Wilson & Cole, 1992). Collins identifies two forms of modeling: modeling of processes as they occur in the world and modeling of expert performance (1988). Modeling physical processes is relatively straightforward. Usually, this can be accomplished with a simulation. The simulation abstractly illustrates how the process unfolds while simultaneously providing reasons for observed changes in the simulation variables. Modeling expert performance is somewhat more difficult. The modeling should include false starts, dead ends, and backup strategies in addition to general solution algorithms (Wilson & Cole, 1992). This maximizes the authenticity of the process. In other words, the novice receives information about how to handle erroneous solutions, not just correct ones.

Supposedly, the benefits of modeling include: 1) seeing expert solutions to problems set by the student, 2) integrating what happens and why, and 3) making parts of a process not normally seen visible (Collins, 1988). Essentially, the modeling/explaining phase serves to structure future instruction.

The next and most important component of the instructional process is *coaching*. The student receives the bulk of the necessary information during coaching. A *scaffolding/fading* paradigm is employed during coaching to insure that the student actively attacks a problem and does not merely wait to be told the correct answer. Basically, scaffolding and fading refer to inter-related processes of providing the student with information as it is needed. The teacher observes the student as he or she tries to solve some problem and provides minimal quantities of information when the student is unable to proceed (Wilson & Cole, 1992).

The academic scaffold is analogous to its real world counterpart. Both are temporary and movable supports which allow individuals to complete a task that would otherwise be impossible. The notion of the academic scaffold is based on the work of Russian cognitive scientist Vygotsky. Vygotsky (1978) hypothesized about the *zone of proximal development*. The opposite sides of the zone represent what the student is capable of doing independently and what the student is capable of doing only under the guidance of the teacher. The role of the teacher is to provide just enough support so that the student begins to navigate the zone. Eventually, as the student demonstrates proficiency, the amount of help is gradually reduced or faded until the student is able to independently solve the problem. The type and amount of knowledge required is at the discretion of the teacher.

The benefits of coaching include: 1) coaching provides help directed at real difficulties, 2) coaching provides help at critical times, 3) coaching provides as much help is needed to accomplish the task, and 4) coaching gives the student new perspectives (Collins, 1988).

The coach must elicit a series of authentic performances from the student in order to diagnose student knowledge and determine the effectiveness of various interventions. Generally, performance is elicited by having the student work through some problem, but there are three specialized forms of performance which are especially important to cognitive apprenticeship. These are *articulation*, *reflection*, and *exploration*.

In *articulation*, students are prompted to think about what they are doing and to provide reasons for their decisions and choice of strategies. Supposedly, this aids in making tacit knowledge explicit (Collins, 1988). Therefore, knowledge about specific aspects of performance which is normally implicit becomes available for other tasks. Articulation allows students to compare solution strategies across situations and develop general solution strategies.

In *reflection*, students analyze their performance and compare it to the performance of others. Performance becomes a subject of study; therefore, students become more aware of their strengths and weaknesses (Collins, 1988). Reflection and articulation are similar, in that both require the student to think about actions and processes which are normally automatic. Presumably, this facilitates metacognitive development.

In *exploration*, students try out alternative hypotheses and strategies in some simulated domain. This activity draws from discovery learning . Discovery learning is less efficient than direct instruction for simple content acquisition, but when the instructional goal is independent problem solving, exploration becomes more important (Wilson & Cole, 1992). Therefore, exploration helps the learner to go beyond the simple and superficial thinking characteristic of approaches which emphasize merely telling students the target content.

Generally, cognitive apprenticeship can be viewed as an approach which uses both showing and telling and requires doing. In this sense, it has the most complex activity structure of any of the approaches addressed here.

Research

Reciprocal teaching has been identified as a successful form of apprenticeship (Collins, Brown, & Newman, 1989; Wilson & Cole, 1992). Briefly, in reciprocal teaching, the teacher and students take turns leading a dialogue about the important features of some text. During discussions about the text, the students are taught four strategies which are designed to foster student comprehension and comprehension monitoring (Palincsar & Brown, 1984). Reciprocal teaching has the three general characteristics of the cognitive apprenticeship activity structure: showing, telling, and doing. Additionally, some of the more specific characteristics of cognitive apprenticeship are preserved. Collaboration, exposure to multiple perspectives, situated learning, and scaffolding are all integral parts of reciprocal teaching.

Palincsar & Brown have shown that reciprocal teaching results in superior achievement and retention over conventional methods for seventh grade problem readers (1984). In a meta-analysis, Rosenshine and Meister (1991) confirmed this conclusion. They reported a median effect size of .52 indicating that reciprocal teaching facilitates the comprehension of text over conventional methods. They found that reciprocal teaching was more effective when cognitive strategy instruction was made explicit, although it did not matter how many strategies were taught.

Atkinson provided an ethnographic demonstration of the effects of apprenticeship training in ar academic setting (1989). She reported that her apprenticeship reading students: 1) liked reading more; 2) liked to share reading more with friends, parents, and teachers; and 3)

demonstrated substantially higher levels of motivation than other students. In another study, English as a Second Language students were taught English and math using either an apprenticeship approach or conventional methods. Scaffolding was provided by giving students help in their native language. The authors found that one year after its introduction, the apprenticeship program helped these students to improve significantly over control students in English and math. They concluded that the use of modeling, scaffolding, evaluation, and collaboration were responsible (Thornburg & Karp, 1992).

Cognitive apprenticeship has also been tested in technical domains. SHERLOCK is a computer-coached practice environment for F-15 repair technicians which utilizes an apprenticeship approach. Lajoie & Lesgold (1989) report that subjects who spent 25 hours on SHERLOCK were as competent as controls who had spent four years on-the-job. Additionally, SHERLOCK subjects solved significantly more problems than their control counterparts, showed more expert-like problem-solving steps, and made fewer incorrect or bad moves in problem-solving than their control counterparts in on-the-job situations.

A similar tutor designed to improve electronics troubleshooting skills using computerized case-based simulations reported similar results (Johnson, 1992). The tutor resulted in significant gains in troubleshooting ability of college electronics students. Subjects with only 5 hours of exposure to the tutor demonstrated a 78% improvement over the control group. Johnson also reported that the experimental subjects were more determined to locate problems and displayed greater confidence in their diagnoses despite the fact that both groups showed equal domain knowledge as measured by a paper-and-pencil test. He concluded that the apprenticeship tutor improved the cognitive and metacognitive processes of the experimental group (Johnson, 1992).

Cognitive apprenticeship is a relatively new approach to instruction. Therefore, there have not been many empirical studies of its effectiveness. Nonetheless, from those that exist, it seems that cognitive apprenticeship is an effective approach in academic and technical settings.

Implications for Intelligent Tutoring Systems

The main criticism of cognitive apprenticeship is that it is resource intensive. That is, it requires a lot of time, money, effort, and materials (Atkinson, 1989). Conversely, this can be viewed as a strength because students receive more detailed and diverse instruction. The computer provides an excellent means of instantiating the approach because the computer can:

- provide a vast array of materials and media choices
- model processes which are not normally visible
- present materials simultaneously using different media
- constantly monitor student performance
- provide individualized coaching and feedback

Cognitive apprenticeship is by far the most comprehensive model of instruction. It includes the important elements of all of the other approaches, such as telling content and doing real world tasks, which the coach can invoke when deemed necessary. For example, research indicates that introductory students perform better under direct instruction, while more advanced

students benefit from some form of discovery (Husic, Linn, & Sloane, 1989). A cognitive apprenticeship-based tutor could simultaneously provide both of these environments. The novices could receive more structured coaching and low-level performance elicitation; and the higher-level students could be in an exploratory mode in which they could formulate hypotheses and discover rules. Further, the mastery spirit is maintained. Coaching individualizes instruction.

Recommendations

In conclusion, it seems logical to use cognitive apprenticeship as our instructional approach, for the following reasons: 1) the inherent limitations of the other approaches, 2) its use does not preclude using techniques characteristic of other approaches, and 3) it is compatible with the goals of intelligent tutoring systems.

Direct instruction and discovery learning have limitations which constrain their use in intelligent tutoring. Direct instruction is an efficient means of transmitting information from teacher to student, but it can encourage passive, idiosyncratic learning. This can result in student misconceptions which are hard to diagnosis and fix. Discovery learning encourages active learning, but it is inefficient. Students spend a lot of time learning a little information. In addition, rates of student failure are increased, which has negative implications for student motivation and attitudes. Table 9 illustrates some specific advantages of cognitive apprenticeship. For example, for the variable *mode(s) of information exchange,* direct instruction and discovery learning utilize only one mode, whereas cognitive apprenticeship utilizes three. Therefore, the nature of the learning in cognitive apprenticeship is more detailed and diverse.

Cognitive apprenticeship is an eclectic approach which does not preclude the use of specific techniques from the other approaches. Therefore, cognitive apprenticeship not only avoids the problems associated with other approaches, but also capitalizes on their strengths. For example, direct instruction primarily utilizes telling; the teacher tells students important information. Discovery learning primarily utilizes doing; students are required to do something. Cognitive apprenticeship incorporates both telling and doing, as well as showing. Therefore, in a sense, it subsumes the other approaches.

Finally, cognitive apprenticeship is compatible with an important goal of intelligent tutoring systems--individualization of instruction. As illustrated in Table 9, individualized instruction is highly emphasized in cognitive apprenticeship. One of its key components is coaching which, like tutoring, provides help: 1) directed at real difficulties, 2) at critical times, and 3) only as needed. Therefore, students are taught according to their individual needs.

During the next phase of this project, we will demonstrate how to integrate the cognitive apprenticeship approach with our knowledge on effective teaching behaviors. The demonstration will take two forms. First, diagrammatic representations of the knowledge will be presented. Second, a system of production rules will be developed. The rule-based representation of this knowledge will be directly transferable to many intelligent tutoring systems.

IV. SELECTION OF KNOWLEDGE REPRESENTATION FORMAT

The selection of a knowledge representation format is an important decision, with significant implications for an intelligent tutoring system's capabilities and overall efficiency. As used here, the term *knowledge representation format* includes: 1) the *techniques* used to represent the knowledge; and 2) the *methodology* for organizing the knowledge in the system.

Review of Knowledge Representation Techniques

A *knowledge representation technique* is a means for expressing knowledge so that a computer can use it. There are a number of different techniques which can be used, and combinations are also possible. However, not all of these techniques are necessarily appropriate for representing tutoring knowledge. In selecting what technique(s) to use, it is important to consider the type of knowledge to be represented and the way that knowledge will be used. Knowledge about mathematical theorem-proving, for example, is represented differently from knowledge about disease diagnosis. A brief description of four of the most frequently mentioned techniques follows.

- *Production rules* - Knowledge is represented by IF-THEN conditional statements. The IF, or condition part, states the conditions which must be present for the rule to be applicable; the THEN, or action part, specifies the action that will take place if the condition is true. The computer reasons by processing rules until it finds one it can use. Production rules are particularly useful when the knowledge to be represented is easily expressed in rule form; they are frequently used for design and/or diagnosis problems in engineering and medicine. Example systems include MYCIN, which aids in diagnosis and selection of therapy for patients with meningitis (Barr & Feigenbaum, 1982); and the VLSI Design Automation Assistant, which helps engineers to design microprocessors (Brachman, 1986).

- *Predicate logic* - Knowledge is represented using predicate logic (e.g., *at(Joe, office)* or *event(landed(Columbus),1492)*). The advantage of using this technique is that standard theorem-proving procedures for this type of reasoning already exist. The computer simply keeps applying rules of deduction until it reaches the goal state. This technique is most useful when the knowledge to be represented can be expressed in mathematically precise terms. It is most commonly used for problem solving and theorem-proving. Examples include FOL, which checks proofs stated in first-order logic; and STRIPS, which helps a robot with the planning problems involved in moving objects and navigating in a cluttered environment (Barr & Feigenbaum, 1982). Two disadvantages of predicate logic are: 1) it can be very slow (Brachman, 1986); and 2) representing certain kinds of information, such as amount of certainty and heuristic information, is difficult (Rich, 1983).

- *Semantic networks* - Knowledge is represented as networks of objects, concepts, or situations which are linked according to their relationships to each other (e.g., *is-a, owned-by*, or *is-a-property of).* The computer reasons by checking the relationships between different nodes in the network. This technique is useful when knowledge can be broken down into small, interconnected units; it is often used for natural language understanding programs (Barr & Feigenbaum, 1982; Brachman, 1986). One of the earliest intelligent tutoring systems, SCHOLAR, used a semantic network to represent and to teach knowledge about South American geography (Carbonell, 1979).

- *Frames and Scripts* - Knowledge is contained in groups of related ideas (like schemata). A restaurant frame, for example, would contain knowledge about things commonly found in restaurants (such as waiters, tables, food, etc.) and expectations for different types of restaurants. A script would contain expectations about the sequence of events that usually occurs when one enters a restaurant. Frames and scripts are like semantic networks in that they can be linked according to relationships; but usually represent more complex forms of knowledge. Frames and scripts are useful for applications requiring recognition or prediction. Examples include CENTAUR, a hybrid system for medical diagnosis, which uses frames to organize production rules into groups relevant to particular diseases (Brachman, 1986); and WHY, an intelligent tutoring system, which uses scripts to represent knowledge about the causes of rain (Stevens, Collins, and Goldin, 1979).

Most intelligent tutoring systems have used production rules to represent teaching knowledge (Rickel, 1989). Exceptions include Carbonell's SCHOLAR (1979), and Stevens, Collins & Goldin's WHY systems, which were described above. Both of these systems are fairly old, however, and it appears that the knowledge representation techniques they used were selected for their fit with the *domain* knowledge, rather than for their ability to represent *pedagogical* knowledge. In fact, Stevens, Collins, and Goldin point out that WHY is quite limited, in terms of its abilities to diagnose student errors and to explain physical processes (both important pedagogical functions), because of its use of a script representation.

Given that the ultimate goal of this effort is to develop one or more generic teaching knowledge templates that can be imported into a variety of tutoring systems, a rule-based representation seems most appropriate. This is because: 1) rules are a widely-used knowledge representation technique which reduces the potential for incompatibility; 2) rules are relatively easy to implement in most programming languages, and programmers are familiar with their use; 3) rules are easy to add, delete, and modify, which will be useful if the template needs to be updated or tailored to the needs of a specific tutoring application; and 4) the knowledge about effective teaching behaviors identified up to this point seems to lend itself naturally to being expressed in rule form.

Review of System Organization Methodologies

A *system organization methodology* is a scheme for structuring and utilizing the knowledge within a system in order to facilitate problem solving (i.e., in order to reach a desired goal state from the current state). Given that production rules will be utilized, there are several different methods for organizing a system (Rich, 1982; Simons, 1984). The most promising (for our purposes) include:

- *List of rules.* In this scheme, the system searches through all the rules until it finds a rule it can use. If the rules are few in number, this is an acceptable approach. However, 1) as the number of rules increases, it becomes difficult to add new rules which do not conflict with existing ones; and 2) it is inefficient to consider all rules at each step of the problem solving process--e.g., sometimes particular clusters of rules apply together, and only when they finish should other rules be considered (Rich, 1982).

- *Model-based.* Rules are used to establish and, over time, correct a model of the relevant world (Simons, 1984). This approach is particularly useful for representing the current state of affairs, or the way a process works. It can also be used for making predictions. In terms of intelligent tutoring systems, a model can be used effectively to represent student behavior or to demonstrate processes in certain domains. However, it is less appropriate for representing knowledge about what instructional activities should be performed next.

- *Blackboard.* Rules pertaining to a particular area of specialization are grouped into *knowledge sources.* Knowledge about the current state is stored in a central area known as a *blackboard.* Whenever a knowledge source has a rule which can apply to changing the current state, that knowledge source becomes activated (i.e., figuratively speaking, it shouts for attention). More than one knowledge source may be activated at any given time. A *control module* monitors the changes on the blackboard, and decides which rules from which knowledge sources should be applied and in what order (Nii, 1986). The blackboard approach is particularly appropriate for applications requiring multi-level reasoning or flexible control of problem solving. However, it has not been widely used, perhaps because: 1) few developers have experience with blackboard applications; and 2) there is not much commercial software available which has been designed for building blackboard applications (Blackboard Technology Group, 1990).

The current version of the Fundamental Skills Tutor for math uses the *list of rules* approach. However, as more rules are added to reflect increasing knowledge about effective teaching, processing the list will gradually become less efficient. Given the number and variety of decisions that a teacher must make while tutoring, the blackboard approach is intuitively appealing (Bumbaca, 1988; Whitaker & Bonnell, 1992). For example, the blackboard could contain knowledge about the current situation (e.g., what has been taught, what approaches have been taken) and the student (e.g., student background knowledge, performance on questions so

far, learning style). Rules could be grouped into knowledge sources based on the types of tutoring decisions they contribute to (e.g., when and how to present information, when to change topics, what instructional medium to use, when and how to assess student performance). Finally, the control module would choose what rules to apply in deciding what instructional actions to take next.

Implementing a blackboard approach would be difficult, however. First, there are currently no tools or shells available for implementing a blackboard architecture on a microcomputer (Murray, personal communication, 1991); which means that a blackboard implementation would have to be built "from scratch" if it were used on a widely available platform. Second, the idea of using a blackboard to dynamically respond to a student is still fairly new, so the concept would probably need to be carefully tested before full-scale implementation could proceed. Significant progress has already been made in this area by Murray (1989a, 1989b), using a tool called BB1, on a Symbolics LISP machine; and by Inui, Miyasaka, Kawamura & Bourne (1989) using FRANZ LISP, OPS5, PEARL, and Flavors on a Micro VAX system.

Trying to implement a blackboard approach, or exploring other possible system organization techniques, would certainly be both challenging and interesting. However, given that the fundamental goal of this effort is to identify effective teaching behaviors and get them into a readily implementable form, such an exploration could potentially absorb resources which can be spent more effectively elsewhere. Since production rules are not incompatible with a blackboard approach, a more practical strategy may be to use the "list of rules" approach for the present. When it becomes more feasible to use blackboards on microcomputers, the rules can always be reorganized.

Recommended Knowledge Representation Format

At the present time, a collection of rules seems to be the easiest way to express the effective teaching knowledge identified in this study. There are certainly more elegant and expressive methods for representing this type of knowledge; in particular, a blackboard type of architecture seems very promising. However, it would be difficult to implement this format on a microcomputer platform. Given 1) that the ultimate goal of this effort is to produce guidance which can be easily implemented in a variety of systems; 2) the popularity of production rules as a form of knowledge representation; and 3) the lack of a standard architecture for intelligent tutoring systems--the development of a set of tutoring rules is indicated. Such a set of rules could be easily modified for use in different intelligent tutoring systems and--after intelligent tutoring system development methodologies become more standardized--reworked into a more efficient format.

V. KNOWLEDGE REPRESENTATION DEMONSTRATION

The goal of this task was to integrate the effective teaching knowledge from Task 1, the instructional approach from Task 2, and the knowledge representation format from Task 3 into a

set of rules which demonstrate how effective teaching knowledge can be implemented on the computer. The purpose was 1) to explore the issues and problems involved in representing teaching knowledge; and 2) to produce a *starter* rule set which can be built upon in future efforts.

The approach taken included the following steps:

- Devised method for visually representing effective teaching behaviors
- Developed list of variables
- Developed rules

Devised Method for Visually Representing Effective Teaching Behaviors

The group of effective teaching behaviors identified during the literature review consisted of isolated, disparate pieces of advice. Before these behaviors could be expressed in a computer-based form, they needed to be structured into a single, cohesive *approach* to teaching. Some method needed to be devised to show what behaviors were included in the approach, how they were sequenced, and the points at which one behavior might be chosen over another.

In addition to providing visual representation, this method also needed to:

- reflect the spirit of cognitive apprenticeship
- be easy to convert to rule form
- incorporate as much of the research on effective teaching behaviors as possible
- be as parsimonious as possible (to simplify rule development)

The research team experimented with a variety of flowcharts and decision trees. Eventually a simple decision tree format was used. The nodes on that decision tree are depicted in outline form in Appendix A. Each node (or *goal*) represents either an action or a decision which will impact a later action.

Issues. Deciding which effective teaching behaviors to represent and how to integrate them was the most difficult part of the rule development process. The following paragraphs describe some of the issues that had to be considered and how they were resolved.

Defining what cognitive apprenticeship includes. The general philosophy behind cognitive apprenticeship is spelled out in the literature, but the nuts-and-bolts details about what a cognitive apprenticeship approach entails at any given point in a teaching interaction is not. The research team decided that this cognitive apprenticeship approach would be an eclectic mix of proven instructional methods, with a bias toward showing and doing (rather than telling). This enabled us to incorporate as much of the research as possible.

Lack of appropriate software tools. The ideal software tool would have allowed easy representation of teaching actions in graphical form, and then automatic conversion to textual, rule-based form. Two software packages which offered these capabilities were reviewed: Automated Knowledge Acquisition/Intelligent Authoring Tool (AKAT), and Task Analysis Rule

Generation Tool (TARGET). However, neither product was complete enough in its current version to be helpful.

In the absence of such software, ordinary drawing software had to be used instead. This made the revision process time-consuming and cumbersome--i.e., every change necessitated redrawing the graph--and made no direct contribution to the rule development process.

Some relevant literature not reviewed. A comprehensive review of all the literature related to this effort would include topics in such areas as educational media, instructional design, teaching methods, learning theory, and human-computer interface design. However, this type of review was not possible within the scope of this project. Because of limited resources, some important areas, such as the literature on screen design and effective use of illustrations, were not reviewed at all.

As stated in Chapter II, however, the team did try to prioritize its investigation of research topics based on each topic's degree of usefulness and implementability. Topics for further research which are particularly significant or urgent will be noted in the recommendations section in the final chapter.

Deciding what to represent. Even in cases when the team was able to review the relevant literature, it was often difficult to apply because the findings were incomplete, speculative, or contradictory. For example, some studies on the effectiveness of advance organizers reported significant improvements in learning with their use, and some did not. Some studies of feedback showed a 24-hour delay to be helpful; and some supported the use of immediate feedback.

In cases where the literature was contradictory, the team identified as many studies as possible, and then triangulated the results. In the case of advance organizers, for example, the team concluded that they do facilitate learning and retention for most learners. In the case of delayed versus immediate feedback, it was found that immediate feedback is helpful in studies which simulate actual teaching situations; whereas delayed feedback is more helpful in studies set in controlled laboratory environments.

In cases where the literature was incomplete or speculative, the team made an educated guess. For example, cognitive apprenticeship does not specifically recommend that students should be able to review relevant materials after missing a question; nor did the team identify research literature which specifically supported or discouraged this practice. However, because it is an option that students normally have in traditional instructional settings, it seemed reasonable to include it. However, we recognize that its inclusion is based on intuitive, rather then empirical or theoretical, justifications.

In some cases, the problem was to decide what *not* to include. For example, in some of the articles on learning strategies (e.g., Dansereau et al., 1975), the authors gave very specific prescriptions for what the teacher should say and when, in teaching certain strategies. This raised the issue of how specific the rule set should be.

The following criteria were developed to determine whether or not to incorporate a given teaching action in the rule set:

1) *Is it supported by research?*
   The team tried to incorporate as many teaching actions supported by research as possible, to take full advantage of the knowledge available.

2) *Is it necessary to include this action to present a complete picture of how the cognitive apprenticeship approach works?*
   For example, diagnosing a student's response was a major goal in the rule set, even though the research literature does not specifically address how to do it, because it is something a teacher always does.

3) *Is it domain-independent?*
   Because the research was intended to provide general guidance, domain specific instructional strategies were excluded.

4) *Is it duplicated by some other action or group of actions already included in the approach?*
   For the sake of parsimony, if an action could be covered by actions already included in the teaching approach, then it was not added. In the case of the learning strategies instruction mentioned above, for example, the team concluded that the essence of the advice could be covered by teaching actions that had already been included.

5) *Is this a design decision?*
   Certain types of instructional decisions (such as which instructional medium to use, content, phrasing, and screen layout) were considered to be *design decisions*, because they can only be made at the time a system is being designed. Because the goal of this project was to produce generic guidance, rather than a specific system, and because of the limited resources available, the research team made little attempt to address these decisions. Instead, effort was concentrated on identifying the *types* of activities and content that should be included in the teaching interaction. It was assumed that specific decisions about content and media could be made by teachers or instructional designers at the time a specific system is being developed. Although this may not be the ideal approach, it at least helps to simplify the problem of deciding what to represent.

Deciding how to represent similar actions. Sometimes teaching actions with similar functions have different names. For example, if a student answers a question incorrectly, and the teacher responds with an extended explanation which contains new information, and then follows with another question, that could be considered to be providing feedback. However, if this response was represented as one type of feedback, then it would duplicate actions dealing with providing instruction and eliciting performance.

In the interests of parsimony, the researchers tried to avoid redundancy as much as possible, while still providing a reasonably complete representation of the teaching process. In the

example above, *feedback* was defined to consist of a short explanation at most, after which a student would be routed back to Goal 1 (Provide situated instruction). At that point, depending on whether or not the student's most recent performance was below a specific criterion level, more explanation could be provided if necessary.

Representing ongoing teaching decisions. The rule set assumes that teaching is a cyclical process, with different decisions or activities occurring at different points in the cycle. However, there are some types of decisions which human teachers appear to make *throughout* the cycle, rather than at any given point. These decisions are often too general to instantiate in the form of rules. For example, human teachers appear to constantly monitor factors such as student fatigue, boredom, level of motivation, and the amount of time left to teach, and to adjust what teaching activities they select accordingly. It was very difficult to figure out how to represent these types of decisions. In addition, there appears to be very little research on how teachers handle this type of decision-making.

Because it was not clear how to represent ongoing teaching decisions, they were left out. Perhaps future research will yield more information about the best way of representing these situations.

Developed List of Variables

In the previous step, the teaching *actions* that would be included in the set of teaching rules were identified. However, in order to write rules, *conditions* also needed to be defined. A human teacher could simply be told "If your student's highly motivated, but hasn't been performing well lately, try action X." However, a computer's vocabulary is much more restricted, so conditions must be defined in precise terms.

Appendix B shows the list of instructional variables that was developed to express the conditions under which actions would be selected. Each variable represents a type of information that is necessary to make a decision. Most variables are set to a default value at the beginning of a course, topic, or session. As the student interacts with the computer more, variable values may change.

Issues. The main issue in developing the list of instructional variables was figuring out how to deal with variables which were difficult for the computer to measure. A variable was considered difficult to measure if 1) there is no good instrument for evaluating it (e.g., motivation); or 2) it is difficult to operationalize (e.g., how the student has been performing "recently").

For variables which were difficult to evaluate, the team made the assumption that the computer could obtain the information somehow (e.g., by having a human teachers manually input information about each student based on their own "gut" assessments). For variables that were difficult to operationalize, the team developed computer-measureable variables which approximated the desired information. For example, to keep track of a student's recent performance, the team developed the LOCPERF variable, which records the student's degree of

success on the past few questions.

Developed Rules

After instructional variables and teaching actions had been defined, the actual writing of the rules was relatively straightforward. Each action on the outline is treated as a *goal* for the computer. A goal becomes the *current goal* whenever certain conditions are met. Teaching actions occur whenever a goal becomes the current goal. Following is a sample walk-through of the rules:

When a student first logs on, Goal 1 needs to become the current goal. To get there, the following rule must fire:

IF TOPICPROGRESS = beginning
THEN GOAL = provide situated instruction [1]
TOPICPROGRESS = early

Translated, this rule says that if a student is just beginning a new topic, then the current goal will become to provide situated instruction (Goal 1). In addition, the value of the variable TOPICPROGRESS is changed to *early*, indicating that the student has just begun learning about the current topic. TOPICPROGRESS is the name of a variable which indicates the degree to which the topic being taught has been presented so far. Its value defaults to *beginning* every time a new topic is introduced.

The next rule that would fire is the following:

IF GOAL = provide situated instruction [1]
THEN GOAL = select type of knowledge [1.1]

This rule says that if the current goal is to provide situated instruction (Goal 1), then the current goal should become to select what type of knowledge to present (Goal 1.1). The purpose of this rule is to move the current goal down from the top level to the level below.

The next rule that would fire is the following:

IF GOAL = select type of knowledge [1.1]
TOPICPROGRESS = early
THEN GOAL = select domain knowledge [1.1.1]

This rule says that if the current goal is to select what type of knowledge to teach (Subgoal 1.1), and the student has just begun learning about the current topic, then the current goal should become to teach knowledge about the domain (Subgoal 1.1.1, as opposed to Subgoal 1.1.2, which is knowledge about learning strategies--which the student would have received if he or she had been in the topic and struggling for some time already).

The next rule that would fire is the following:

IF GOAL = select domain knowledge [1.1.1]
THEN KTYPE = domain

This rule causes the value of a variable named KTYPE, which represents the type of knowledge which will be taught, to *domain*. The actual teaching does not get done at this point; that happens in a later rule. Notice also that this rule does not change the value of the current goal. This is accomplished by the following rule:

IF GOAL = select domain knowledge [1.1.1]
THEN GOAL = select method of presentation [1.2]

This rule says that if the current goal is to select domain knowledge (Subgoal 1.1.1), then the current goal should become to select a method of presentation (Subgoal 1.2). Notice that this rule gets the system back up one level and advances it to the next subgoal within that level.

Computer-savvy readers may notice that this rule set is not really complete. This rule set was developed for demonstration purposes only, to suggest how a rule set *might* look; it is not intended to be executable.

Issues. The following paragraphs describe issues that had to be addressed during the rule development process.

Context of use unknown. The context in which these rules will ultimately be used was not clear. The following assumptions were made for the purposes of the demonstration:

1) A curriculum, consisting of a list of topics, has already been defined. The rule set teaches one topic from this curriculum until it is mastered, then moves to the next topic.

2) Certain information is readily available, such as background knowledge about the student and knowledge about the nature of the subject to be taught. In an actual implementation of an intelligent tutoring system, this knowledge would need to specified for the system before students ever log on.

3) Information will be collected and updated as needed in the course of a teaching session. Although this rule set makes frequent references to what values variables need to have before an action can take place, it makes minimal provision for housekeeping--i.e., for initializing those variables or updating them to reflect changes in student performance, progress within a topic, and so on. In an actual intelligent tutoring system, programmers would need to specify how and when information will be collected and updated.

4) Decisions about matters such as screen design, reading level, instructional media, and how a topic will be presented, are for the most part left to the teacher or instructional designer. This set of rules only provides a generic framework which suggests what teaching actions should take place, and in what order. More specific teaching decisions can only be made when trying to design a system for a particular application.

5) A criterion-based approach to instruction is desired. That is, a student will be taught until his or her performance exceeds a specified criterion.

6) Criterion values for variables have been defined. In many cases, this rule set makes decisions based on whether the values of certain variables are ***above*** or ***below criterion***. In an actual implementation, the range of possible values for these variables would need to be defined, and criterion values would need to be specified.

Indicating completion of goals. In an executable rule set, after firing a rule, the system would automatically start at the top of the rule stack in looking for the next rule to fire. There needs to be some way of indicating that a goal has been completed, in order to prevent the system from firing the same rule again and again in some cases. The research team tried to provide a mechanism for this, but quickly got bogged down. Since this is a housekeeping rather than a teaching issue, and because we did not know what software will be used to program these rules anyway, we decided to just assume it would somehow be taken care of.

Addressing all possible conditions. An executable rule set would also somehow encompass all possible combinations of goals and conditions; that is, there would always be a rule that would fire until it is time for the end of the teaching session. However, the demonstration rule set primarily represents information about effective teaching behaviors. Again this is because the requirement was only to demonstrate how effective teaching behaviors could be represented in rule-based form, not to develop a working set of rules.

Quantifying criterion values for variables. The educational research literature at best indicates what factors are important to monitor, and generally what implications different levels of those factors have for teaching methods. For example, the literature suggests that as a student's mastery of a topic increases, the amount of scaffolding provided by the system should decrease (i.e., high mastery requires little or no scaffolding; low mastery requires high scaffolding). However, computers need to be told precisely how much scaffolding to provide at precisely what level of mastery. Because the application of this general principle may vary over different domains or teaching situations, the research team did not attempt to quantify levels of values for variables. Instead, variable values were referred to as being ***high***, ***medium***, ***low***, ***above criterion***, or *below criterion*.

VI. CONCLUSIONS AND RECOMMENDATIONS

The educational research literature is a rich source of effective teaching knowledge, much of which is applicable to intelligent tutoring systems. This study was a preliminary attempt to tap this knowledge and translate it into a computer-based form. We hope that the outputs from this effort will be useful as: 1) information about effective teaching behaviors for both educators and ITS developers; 2) lessons learned for others who may wish to use the integrative approach to ITS development; and 3) a starting point for developing the tutoring component of intelligent tutoring systems.

Much more needs to be known about how to individualize instruction. For every instructional technique or strategy reviewed for this project, the research about how to target it for particular instructional situations was inconclusive. What is most needed is more studies which examine how various aptitudes, traits, and treatments interact. These studies could be used to tease out the differential effects of variables when they appear in combination.

It should be noted however, that attempts to individualize instruction should be made with caution. Programs which adapt instruction to individual learners have often failed to demonstrate a significant improvement over ordinary non-adaptive instruction (Corno & Snow, 1986; Doyle & Rutherford, 1984). Many of these studies have been conducted with classroom-based, not computer-based, programs, and may therefore not be applicable to one-on-one situations. Still, ITS developers should remember that more individualization 1) may not necessarily be better; and 2) may not necessarily be cost-effective. A smart approach may be to initially individualize instruction based on variables which have been shown to have a strong correlation with effective learning (e.g., IQ). It may also be more cost-effective initially to take Shute's approach of varying instructional treatments based on aptitudes, rather than to attempt a model-tracing approach (Shute, 1991). Finally, it is important to remember that if the core instructional approach selected is either very good or very poor, individualization factors will probably have no significant effect.

Following are some suggestions for research activities which could build upon the results of this study. First, continue reviewing and summarizing effective teaching behaviors from the educational research literature, such as screen design, media selection, effective use of visuals (e.g., graphics, animation, video), and computer-based assessment methods. Incorporating teaching rules from these areas would help an ITS to make more effective decisions about presentation of information.

Second, try instantiating some of the rules and principles identified in this effort within an intelligent tutoring system (e.g., the Fundamental Skills Science Tutor). This will help point out areas for further refinement.

Third, develop an operational rule set. Ideally, this rule set should serve as a domain-independent instructional template, which can be dropped into a variety of intelligent tutoring systems, with minimal revisions.

Fourth, consider ways of integrating this rule set with the Advanced Instructional Design Advisor (AIDA). Perhaps AIDA could serve as an intelligent front-end to the tutoring template, by collecting and structuring domain expertise into a form the template can use.

Fifth, support research in areas which will enhance the template's capacity to individualize instruction. Specifically, 1) identify what the criterion values for doing certain actions should be; and 2) describe how constructs such as intelligence, cognitive style, motivation, and self-efficacy (and combinations thereof) interact with different types of instructional treatments.

Sixth, continue to track hardware and software developments which might allow use of

more powerful knowledge representation formats, such as blackboard architectures. These would make ITSs more capable, and make the task of representing teaching knowledge easier.

Seventh, develop rule sets for other instructional approaches, such as direct instruction and discovery learning. These rule sets can then be instantiated and compared to the cognitive apprenticeship approach.

Eighth, develop techniques to make the tutoring capabilities self-improving (i.e., try to utilize machine learning). It would be ideal if the tutor could recognize that certain types of teaching actions are ineffective with a particular student, alter its approach accordingly, and then use the altered approach subsequently in similar situations.

REFERENCES

Aiken, L. R. (1991). Psychological Testing and Assessment. Boston, MA: Allyn and Bacon.

Albertson, L. M. (1986). Personalized feedback and cognitive achievement in computer assisted instruction. Journal of Instructional Psychology, 13, 55-57.

Ames, C. & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation process. Journal of Educational Psychology, 80, 260-267.

Anderson, R. C. & Armbruster, B. B. (1990). Some maxims for learning and instruction. Teachers College Record, 91, 397-408.

Anderson, J.R., Boyle, C.F., & Reiser, B.J. (1985). Intelligent tutoring systems. Science, 228, 456-462.

Applebee, A. N. & Langer, J. A. (1983). Instructional scaffolding: Reading and writing as natural language activities. Language Arts, 60, 168-175.

Atkinson, E. (1989). Assessing the apprenticeship approach in the classroom. Reading, 23, 17-22.

Ausubel, D. A. (1977). The facilitation of meaningful verbal learning in the classroom. Educational Psychologist, 12, 162-178.

Bandura, A. (1989). Regulation of cognitive processes through perceived self-efficacy. Developmental Psychologist, 25, 729-735.

Bandura, A. & Schunk, D. (1981). Cultivating competence, self-efficacy and intrinsic interest through proximal self-motivation. Journal of Personality and Social Psychology, 41, 586-598.

Barr, A. & Feigenbaum, E.A. (1982). The handbook of artificial intelligence (Vol. 1). Los Altos, CA: William Kaufmann, Inc.

Bellezza, F. S. (1983). The spatial-arrangement mnemonic. Journal of Educational Psychology, 75, 830-837.

Berlyne, D. E. (1961). Conflict, Arousal, and Curiosity. New York: McGraw-Hill.

Billings, D. M. & Cobb, K. L. (1992). Effects of learning style preferences, attitude, and GPA on learner achievement using computer-assisted interactive videodisc instruction. Journal of Computer-Based Instruction, 19, 12-16.

Blackboard Technology Group (1990, Summer). A generic framework for blackboard applications. AI Review, pp. 21-24.

Bloom, B. S. (1984). The 2 sigma problem: the search for methods of group instruction as

effective as one-to-one tutoring. Educational Researcher, 13(6), 4-16.

Bloom, B. S. (1976). Human Characteristics and School Learning. New York: McGraw-Hill.

Borko, H. & Shavelson, R. J. (1990) Teacher decision making. In B. F. Jones & L. Idol (Eds.), Dimensions of thinking and cognitive instruction (pp. 311-346). Hillsdale, NJ: Lawrence Erlbaum Associates.

Bouffard-Bouchard, T. (1990). Influence of self-efficacy on performance in a cognitive task. Journal of Social Psychology, 130, 353-363.

Brachman, R.J. (1988). Basics of knowledge representation and reasoning. AT&T Technical Journal, 67(1), 7-24.

Brophy, J. (1986). Teacher influences in student achievement. American Psychologist, 41, 1069-1077.

Brown, J. S., Collins, A. & Duguid, P. (1989). Situational cognition and the culture of learning. Educational Researcher, 18, 32-42.

Brown, K. J., Trathan, W., & Dole, J. A. (1992, April). Individual differences in student mediation of strategy instruction: A case study. Paper presented at the Annual Meeting of the American Eduational Research Association. San Francisco, CA:.

Brown, J.S. & Burton, R.R. (1978). Diagnostic models for procedural bugs in basic mathematical skills. Cognitive Science, 2, 155-192.

Bruner, J. S. (1961). The act of discovery. The Harvard Educational Review, 31, 21-32.

Bumbaca, F. (1988). Intelligent computer-assisted instruction: A theoretical framework. International Journal of Man-Machine Studies, 29, 227-255.

Campione, J. C. (1987). Metacognitive components of instructional research with problem learners. In F. E. Weinert, & R. H. Kluwe (Eds.), Metacognition, motivation, and understanding. Hillsdale, NJ: Lawrence Erlbaum Ass.

Carbonell, J.R. (1970). AI in CAI: An artificial-intelligence approach to computer-assisted instruction. IEEE Transactions on Man-Machine Systems, 11 (4), 190-202.

Carlson, R. D. & Grabowaki, B. L. (1992). The effects of computer self-efficacy on direction following behavior in computer assisted instruction. Journal of Computer-Based Instruction, 19, 6-11.

Carrier, C. (1984). Do learners make good choices? Instructional Innovator, 48, 15-17.

Carrier, C. A., Davidson, G. V., Higson, V., & Williams, M. D. (1984). Selection of options by field independent and dependent children in computer-based concept lesson. Journal of Computer-Based Instruction, 11, 49-54.

Clancey, W. J. (1992). Representations of knowling: In defense of cognitive apprenticeship. Journal of Artificial Intelligence in Education, 3, 139-168.

Clancey, W.J. (1984). Methodology for building an intelligent tutoring system. In W. Kintsch, J.R. Miller, & P.G. Polson (Eds.), Methods and tactics in cognitive science. Hillsdale, NJ: Erlbaum.

Clariana, R. B. (1990). A comparison of answer till correct feedback and knowledge of correct response feedback under two conditions of contextualization. Journal of Compuer Based Instruction, 17, 125-129.

Clariana, R. B., Ross, S. M., & Morrison, G. R. (1992). The effects of different feedback strategies using computer-administered multiple choice questions as instruction. Educational Training, Research and Design, 39, 5-17.

Clark, C. M. & Yinger, R. J. (1979). Teacher's thinking. In P. L. Peterson & H. J. Walberg (Eds.), Research on Teaching: Concepts, Findings, and Implications. Berkley, CA: McCutchan.

Clarke, J. H. (1991). Using visual organizers to focus thinking. Journal of reading, 34, 526-534.

Cliburn, Jr. J. W. (1990). Concept maps to promote meaningful learning. Journal of College Science Teaching, 19, 212-217.

Cognition and Technology Group at Vanderbilt (CTCV). (1992). The Jasper experiment: An exploration of issues in learning and instructional design. Educational Technology, Research, & Development, 40, 65-80.

Collins, A., Brown, J. S., & Newman, S. E. (1989). Cognitive apprenticeship: Teaching the craft of reading, writing, and mathematics. In L. B. Resnick (ed.). Knowing, Learning, and Instruction: Essays in Honor of Ro ..rt Glaser. Hillsdale, NJ: Lawerence Erlbaum Associates.

Collins, A. (1988). Cognitive apprenticeship and instructional technology. Cambridge, MA: BBN Laboratories, Inc.

Collins, M., Carnine, D. & Gersten, R. (1987). Elaborated corrective feedback and the acquisition of reasoning skills: A study of computer-assisted instruction. Exceptional Children, 54, 254-262.

Collins, A., Warnock, E.H., & Passafiume, J.J. (1975). Analysis and synthesis of tutorial dialogues. In G.H. Bower (Ed.), The psychology of learning and motivation (Vol. 9, pp. 49-87). New York: Academic Press.

Corno, L., & Snow, R. E. (1986). Adapting teaching to individual differences among learners. In M. C. Wittrock (Ed.), Handbook of Research on Teaching (3rd ed.). New York: MacMillan.

Dansereau, D. F., Long, G. L., McDonald, B. A., Actkinson, T. R., Ellis, A. M., Collins, K., Williams, S., & Evans, S. H. (1975). Effective learning strategy training program: Development and assessment. (Report No. AFHRL-TR-75-41). Colorado: Lowry AFB.

Davis, G. A. (1983). Educational Psychology: Theory and Practice. Reading, MA: Addison-Wesley.

Doyle, W. & Rutherford, B. (1984). Classroom research on matching learning and teaching styles. Theory into Practice, 23, 20-25.

Duffy, T. M. & Jonassen, D. H. (1991, May). Constructivism: New implications for instructional technology. Educational Technology, 7-12.

Dweck, C. S. (1986). Motivational processes affecting learning. American Psychologist, 41, 1040-1048.

Festinger, L. (1957). A Theory of Cognitive Dissonance. Evanston, IL: Row, Peterson.

Fox, B. A. (1991). Cognitive and interactional aspects of correction in tutoring. In P. Goodyear (Ed.), Teaching Knowledge and Intelligent Tutoring (pp. 149-172). Norwood, NJ: Ablex Publishing Corporation.

Frank, B. M. (1984). Effect of field independence-dependence and study technique on learning from a lecture. American Educational Research Journal, 21, 669-678.

Gagne, E. D. (1985). The cognitive psychology of school learning. Boston, MA: Little, Brown, and Co.

Gall, M. D. (1970). The use of questions in teaching. Review of Educational Research, 40, 707-721.

Garner, R. (1990). When children and adults do not use learning strategies: Toward a theory of settings. Review of Educational Research, 60, 517-529.

Glades, D. K. & Smith, P. J. (1990). Building and intelligent tutoring system: Some guidelines from a study of human tutors. Proceedings of the 34 th Human Factors Society, 1407-1411.

Goodyear, P. (1991). Research on teaching and the design of intelligent tutoring systems. In P. Goodyear (Ed.), Teaching knowledge and intelligent tutoring. Norwood, NJ: Ablex.

Graesser, A. C. (1992). Questioning mechanisms during complex learning (Report No. R & T 4422548). Arlington, VA: Office of Naval Research.

Grapko, M. P. (1972). A comparison of open space and traditional classroom structures according to independence measures in children, teachers' awareness of children's personality variables, and children's academic progress. (Final Report). Toronto: Ontario

Department of Education. ERIC Document Reproduction Service No: 088 180).

Hakstian, A. R. & Gale, C. A. (1979). Validity studies using the comprehensive ability battery: Performance in conjunction with personality and motivational traits. Educational and Psychological Measurement, 39, 389-400.

Hansen, J. B. (1974). Effects of feedback, learner control, and cognitive abilities on state anxiety and performance in a computer-assisted instruction task. Journal of Educational Psychology, 66, 247-254.

Harter, S. (1981). A new self report scale of intrinsic versus extrinsic orientation in the classroom: Motivation and informational components. Developmental Psychology, 17, 300-312.

Heckel, R. V., Allen, S. S., & Stone, P. A. (1981). A comparison of self-rated high and low success problem solvers. Journal of Psychology, 107, 173-176.

Heinze-Fry, J. A. & Novak, J. D. (1990). Concept mapping brings long term movement towards meaningful learning. Science Education, 74, 461-472.

Hermann, G. (1969). Learning by discovery: A critical review of studies. Journal of Experimental Education, 38, 58-72.

Holloway, R. L. (1978). Task selection and locus of control in two ability groups' recall. Contemporary Educational Psychology, 3, 118-126.

Husic, F. T., Linn, M. C, & Sloane, K. D. Adapting instruction to the cognitive demands of learning to program. Journal of Educational Psychology, 81, 570-583.

Ilgen, D. R. & Moore, C. F. (1987). Types and choices of performance feedback. Journal of Applied Psychology, 72, 401-406.

Inui, M., Miyasaka, N., Kawamura, K., and Bourne, J.R. (1989). Development of a model-based intelligent training system. Future Generation Computer Systems, 5(1), 59-69.

Jelsma, O. & Van-Merrienboer, J. J. (1989). Contextual interference: Interactions with reflection-impulsivity. Perceptual and Motor Skills, 68, 1055-1064.

Johnson, D. D., Dittleman, S., & Heimlich, J. (1986). Semantic mapping. The Reading Teacher, 39, 778-783.

Johnson, S. D. (1992, April). The effectiveness of a computer coached practice environment for teaching problem solving in complex technical domains. Paper presented at the Annual Meeting of the American Educational Research Association, San Francisco, CA.

Kagan, J. (1965). Impulsive and reflective children: Significance and conceptual tempo. In J. D. Krumboltz (Ed.), Learning and the Educational Process. Chicago, IL: Rand-McNally.

Karrer, U. (1991). Impacts of courseware and student characteristics on learning achievement:

Results of an empirical study. Journal of Computer Assisted Learning, 7, 18-33.

Keim-Abbott, S., & Abbott, R. D. (1977). Moderation of achievement prediction in an elementary school metric curriculum by trait x instructional method interactions. Educational and Psychological Measurement, 37, 481-486.

Kelley, L. (1992, April). Making the unfamiliar familiar: Problem solving heuristics as a means of confronting students' misconceptions in algebra. Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Kenzie, M. B., Sullivan, H. J. & Berdel, R. L. (1988). Learner control and achievement in science computer assisted instruction. Journal of Educational Psychology, 80, 299-303.

Klein, J. D. & Keller, J. M. (1990). Influence of student ability, locus of control, and type of instructional control on performance and confidence. Journal of Educational Research, 83, 140-146.

Klein, J. D. & Freitag, E. T. (1992, March). Training students to utilize self-motivational strategy. Educational Technology, pp. 44-48.

Kloster, A. M. & Winne, P. H. (1989). The effects of different types of organizers on students' learning from text. Journal of Educational Psychology, 81, 9-15.

Krahn, C. G., & Blancher, M. C. (1986). Using an advance organizer to improve knowledge application by medical students in computer-based clinical simulations. Journal of Computer-Based Instruction, 13, 71-74.

Kulhavy, R. W., White, M. T., Topp, B. W., Chan, A. L. & Adams, J. (1985). Feedback complexity and corrective efficiency. Contemporary Educational Psychology, 10, 285-291.

Kulik, J. A., Kulik, Chen-Lin C. & Cohen, P. A. (1979). A meta-analysis of outcome studies of Keller's personalized system of instruction. American Psychologist, 34, 307-318.

Kulik, J. A. & Kulik, Chen-Lin C. (1988). Timing of feedback and verbal learning. Review of Educational Research, 58 (1), 79-97.

Lajoie, S. P., & Lesgold, A. (1989). Apprenticeship training in the workplace: Computer-coached practice environment as a new form of apprenticeship. Machine-Mediated Learning, 3, 7-28.

Lambiotte, J. G., Peel, J., & Dansereau, D. F. (1992, April). Knowledge maps as review devices: Like 'em or not. Paper presented at the annual meeting of the American Educational Research Association. San Francisco, CA.

Larson, R. E. (1992). Relationship of learning style to the effectiveness and acceptance of interactive video instruction. Journal of Computer-Based Instruction, 19, 17-21.

Levin, J. R., Morrison, C. R., McGivern, J. E., Mastropieri, M. A. & Scruggs, T. E. (1986). Mnemonic facilitation of text-embedded science facts. American Educational Research Journal, 23, 489-506.

Levine, J. M., & Schneider, W. (1989). Feedback effects in computer-based skill learning. (Report No. ONR-1142CS). Arlington, VA: Office of Naval Research.

Lewis, M. & Cooney, J. (1987). Attributional and performance effects of competitive and individualistic feedback in computer assisted mathematics instruction. Computers in Human Behavior, 3, 1-13.

Linn, M. C. & Clancey, M. J. (1990, April). Designing instruction to take advantage of recent advances in understanding cognition. Academic Computing, 20-41.

Littman, D. C., Pinto, J., & Soloway, E. (1985). Observations on tutorial expertise. Paper presented in Proceedings of IEEE Computer Society Symposium on Expert Systems in Government.

Loper, A. B., & Murphy, D. M. (1985). Cognitive self- regulatory training for underachieving children (ch.6). In D. L. Forrest-Pressley, G. E. MacKinnon, & T. G.Waller (Eds.), Metacognition, Cognition, and Human Performance: Volume 2, Instructional Practices. New York: Academic Press, Inc.

Luiten, J., Ames, W., & Ackerson, G. (1980). A meta-analysis of the effects of advance organizers on learning and retention. American Educational Research Journal, 17, 211-218.

Maslow, A. H. (1970). Motivation and Personality. (2nd ed.). New York: Harper & Row.

McKendree, J. (1990). Effective feedback content for tutoring computer skills. Human Computer Interaction, 5, 381-413.

Meece, J., Blumenfeld, P., & Hoyle, R. (1988). Students' goal orientations and cognitive engagement in classroom activities. Journal of Educational Psychology, 80, 514-523.

Meng, K., & P. D. (1991). Field dependence and contextual organizers. Journal of Educational Research, 84, 183-189.

Merrill, D. M. (1991, May). Constructivism and instructional design. Educational Technology, pp. 45-53.

Merrill, D. C., Reiser, B. J., Ranney, M., & Trafton, J. G. (1992). Effective tutoring techniques: A comparison of human tutors and ITS's. The Journal of the Learning Sciences, (in press).

Merrill, J. (1987). Levels of questioning and forms of feedback: Instructional factors in courseware design. Journal of Computer-Based Instruction, 14, 18-22.

Messick, S. (1984). The nature of cognitive styles: Problems and promise in educational practice. Educational Psychologist, 19, 59-74. (noted in pre-assessment summary)

Miller, G. E. (1985). The effects of general and specific self-instruction. Reading Research Quarterly, 20, 616-628.

Moreira, M. A. (1985). Concept mapping: An alternative strategy for evaluation. Assessment and Evaluation in Higher Education, 10, 159-168.

Mory, E. (1992, April) The use of response certitude in adaptive feedback: Effects on student performance, feedback study time and efficiency. Paper presented at the Annual Meeting of the American Educational Research Association, San Francisco, CA.

Murray, W.R. (1989a). Dynamic instructional planning in the BB1 blackboard architecture (Technical Report No. R-6168). Santa Clara, CA: FMC Corporation.

Murray, W.R. (1989b). A blackboard-based dynamic instructional planner (Contract No. N00014-86-C-0487). Santa Clara, CA: FMC Corporation.

Naveh-Benjamin, M. (1991). A comparison of training programs intended for different types of test anxious students: Further support for an information-processing model. Journal of Educational Psychology, 83, 134-139.

Nii, H.P. (1986, Summer). Blackboard systems: The blackboard model of problem solving and the evolution of blackboard architectures (Part 1). The AI Magazine, pp. 38-53.

Novak, J. D., Gowin, D., & Johansen, G. (1983). The use of concept mapping and knowledge vee mapping with junior high school science students. Science Education, 67, 625-645.

Novak, J. D. (1985). Learning How To Learn. New York: Cambridge University Press.

Nuthall, G. & Snook, I. (1973). Contemporary models of teaching. In R. M. W. Travers (Ed.), Second handbook of Research on Teaching, (pp. 47-76). Chicago, IL: Rand McNally.

O'Neil, H.F., Slawson, D.A., & Baker, E.L. (1991). Design of a domain-independent problem-solving instructional strategy for intelligent computer-assisted instruction. In H. Burns, J.W. Parlett, & C.L. Redfield (Eds.), Intelligent tutoring systems: Evolutions in design. Hillsdale, NJ: Erlbaum.

Ornstein, A. C. (1988). Questioning: The essence of good teaching-Part II. NASSP Bulletin, 72, 72-80.

Otto, P. B. (1991). Finding an answer in questioning strategies. Science and Children, 28, 44-47.

Palincsar, A. S., & Brown, A. L. (1984). Reciprocal teaching of comprehension-fostering and comprehension-monitoring activities. Cognition and Instruction, 1, 117-175.

Palincsar, A. S. (1986). The role of dialogue in providing scaffolded instruction. Educational

Psychologist, 21, 73-98.

Pankratius, W. J. (1990). Building an organized knowledge base: Concept mapping and achievement in secondary school physics. Journal of Research in Science Teaching, 27, 315-333.

Paris, S. S., Cross, . R. & Lipson, M. Y. (1984). Informed strategies for learning: A program to improve children's reading awareness and comprehension. Journal of Educational Psychology, 76, 1239-1252.

Peterson, P. L. (1979). Direct instruction reconsidered. In P. L. Peterson & H. L. Walberg (Eds.). Research on Teaching: Concepts, Findings, and Implications. Berkley, CA: McCutchan.

Pintrich, P. R., & DeGroot, E. V. (1990). Motivational and self-regulate learning components of classroom academic performance. Journal of Educational Psychology, 82, 33-40.

Pressley, M. (1986). The relevance of the good strategy user model to the teaching of mathematics. Educational Psychologist, 21, 139-161.

Rankin, R. J. & Treper, J. (1978). Retention and delay of feedback in a computer-based instructional task. Journal of Experimental Education, 46, 67-70.

Rich, E. (1983). Artificial intelligence. New York: McGraw-Hill.

Rickel, J.W. (1989). Intelligent computer-aided instruction: A survey organized around system components. IEEE Transactions on Systems, Man, and Cybernetics, 19(1), 40-57.

Riley, J. (1986). The effects of teachers' wait time and knowledge comprehension questioning on science achievement. Journal of Research in Science Teaching, 23, 335-342.

Rosenshine, B., & Meister, C. (1991, April). Reciprocal teaching: A review of nineteen experimental studies. Paper presented at the annual meeting of the American Educational Research Association, Chicago, IL.

Rosenshine, B. V. (1979). Content, time and direct instruction. In P. L. Peterson & H. J. Walberg (Eds.), Research in Teaching: Concepts, Findings, and Implications. McCutchan Publishing.

Ross, S. M. & Rakow, E. A. (1981). Learner control versus program control as adaptive strategies for selection of instructional support on math rules. Journal of Educational Psychology, 73, 745-753.

Salas, S. & Dickinson, D. (1990). The effect of feedback and three different types of corrections on student learning. Journal of Human Behavior and Learning, 7, 13-19.

Sandberg, J. & Wielinga, B. (1992). Situated cognition: A paradigm shift? Journal of Artificial Intelligence in Education, 3, 129-138.

Sassenrath, J. M. (1975). Theory and results of feedback and retention. Journal of Educational Psychology, 67, 894-899.

Schank, R. C., & Jona, M. Y. (1991). Empowering the student: New perspectives on the design of teaching systems. The Journal of the Learning Sciences, 1, 7-35.

Schloss, P. J., Wisniewski, L. & Cartwright. G. P. (1988). The differential effect of learner control and feedback in college students' performance on CAI modules. Journal of Educational Computing Research, 4, 141-10.

Schoenfeld, A. H., Gamoran, M., Kessel, C., & Leonard, M. (1992, April). Toward a comprehensive model of human tutoring in complex subject matter domains. Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Schunk, D. H. (1984a, April). Self-efficacy and classroom learning. Paper presented at the annual meeting of the American Educational Research Association, New Orleans, LA.

Schunk, D. H. (1984b). Self-efficacy perspective on achievement behavior. Educational Psychologist, 19, 48-58.

Schunk, D. H. (1990). Goal setting and self-efficacy during self-regulated learning. Educational Psychologist, 25,71-86.

Schutz, P. A. (1992, April). Boundary conditions on the relationship between feedback and response certitude during the learning process. Paper presented at the Annual Meeting of the American Educational Research Association, San Francisco, CA.

Shavelson, R. J., & Stern, P. (1981). Research on teachers' pedagogical thoughts, judgments, decisions, and behavior. Review of Educational Research, 51, 455-498.

Shuell, T. J. (1988). The role of the student in learning from instruction. Contemporary Educational Psychology, 13, 276-295.

Shute, V. J. (1991, October). How to build more intelligent tutoring systems. Paper presented at the 33rd Annual Conference of the Military Testing Association Proceedings. San Antonio, TX.

Simons, G.L. (1984). Introducing artificial intelligence. Manchester, England: NCC Publications.

Slavin, R. E. (1987). Mastery learning reconsidered. Review of Educational Research, 57, 175-213.

Smith, K. A. (1988). The nature and development of engineering expertise. European Journal of Engineering Education, 13, 317-330.

Stallings, J. A. & Kaskowitz, D. (1974). Follow-Through Classroom Observation Evaluation

1972-1973. Menlo Park, CA: Stanford Research Institute

Steinberg, E. R. (1989). Cognition and learner control: A literature review. Journal of Computer-Based Instruction, 16, 117-121.

Stensvold, M. S. & Wilson, J. T. (1990). The interaction of verbal ability with concept mapping in learning from a chemistry laboratory activity. Science Education, 7, 473-489.

Stevens, A., Collins, A. & Goldin, S.E. (1979). Misconceptions in student's understanding. International Journal of Man-Machine Studies, 11, 145-156.

Stone, C. L. (1983). A meta analysis of advance organizer studies. Journal of Experimental Education, 51, 194-199.

Sturges, P. T. (1978). Delay of informative feedback in computer-assisted testing. Journal of Educational Psychology, 70, 378-387.

Tait, K., Hartley, J. R. & Anderson, R. C. (1973). Feedback procedures in computer assisted arithmetic instruction. British Journal of Educational Psychology, 43, 161-171.

Tennyson, R. D. & Park, O. C. (1987). Artificial intelligence and computer-based learning. In R. M. Gagne (Ed.), Instructional Technology: Foundations. (pp. 319-342). Hillsdale, NJ: Lawerence Erlbaum Associates.

Thornberg, D. G., & Karp, K. S. (1992, April). Resituating mathematics and science instruction for language different students. Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Tobin, K. (1986). Effects of teacher wait time on discourse characteristics in mathematics and language arts classes. American Educational Research Journal, 23, 191-200.

Tobin, K. (1987). The role of wait time in higher cognitive level learning. Review of Educational Research, 57, 69-95.

Tobin, K. (1984). Effects of extended wait time on discourse characteristics and achievement in middle school grades. Journal of Research in Science Teaching, 21, 779-791.

Vygotsky, L.S. (1978). Mind and society: The development of higher psychological processes. In M. Cole, V. John-Steiner, S. Scribner, E. Souberman (Eds.), Mind in Society: The Development of Higher Psychological Processes. Cambridge, MA: Harvard University Press.

Wager, W. & Wager, S. (1985). Presenting questions, processing responses and providing feedback in CAI. Journal of Instructional Development, 8, 2-8.

Walberg, H. L. (1991). Productive teaching and instruction: Assessing the knowledge base. Effective Teaching: Current Research. Berkeley, CA: McCutchan Publishing Co.

Walczyk, J. J. & Hall, V. C. (1989). Is the failure to monitor comprehension an instance of cognitive impulsivity? Journal of Educational Psychology, 81, 294-298.

Weiner, B. (1980). Human Motivation. New York: Holt, Rinehart, & Winston.

Weiner, B. (1979). A theory of motivation for some classroom experiences. Journal of Educational Psychology, 71, 3-25.

Weinstein, C. E. & Mayer, R. E. (1986). The teaching of learning strategies (chapter 11). In M. C. Wittrock (Ed.), Handbook of Research of Teaching (3rd ed.). New York: MacMillan.

Wenger, E. (1987). Artificial intelligence and tutoring systems: Computational and cognitive approaches to the communication of knowledge. Los Altos, CA: Morgan Kaufmann.

Whitaker, E.T. & Bonnell, R.D. (1992). A blackboard model for adaptive and self-improving intelligent tutoring systems. Journal of Artificial Intelligence in Education, 3, 3-27.

White, R. W. (1959). Motivation reconsidered: The concept of competence. Psychological Review, 66, 297-333.

Wilson, B. J. & Cole, P. (1991). A review of cognitive teaching models. Educational Technology, Research and Development, 39, 47-64.

Winne, P. H., & Marx, R. W. (1980). Matching students' cognitive responses to teaching skills. Journal of Educational Psychology, 72, 257-264.

Winne, P. H. (1989). Theories of instruction and of intelligence for designing artificially intelligent tutoring systems. Educational Psychologist, 24, 229-259.

Yee, P.J. (1989). A qualitative study of three expert tutoring sessions. Unpublished Master's thesis. Austin, TX: The University of Texas at Austin.

Young, A. J., Arbreton, A. J. A. & Midgley, C. (1992, April). All content areas may not be created equal: Motivational orientation and cognitive strategy use in four academic domains. Paper presented at the Annual Meeting of the American Educational Research Association, San Francisco, CA.

Zeitz, L. E. & Anderson-Inman, L. (1992). The effects of computer-based formative concept mapping on learning high school science. Paper presented at the annual meeting of the American Educational Research Association. San Francisco, CA. April.

Zimmerman, B. J., (1989). A social cognitive view of self-regulated academic learning. Journal of Educational Psychology, 81, 329-339.

APPENDIX A

OUTLINE OF TEACHING BEHAVIORS INCLUDED IN RULE SET

OUTLINE OF TEACHING BEHAVIORS INCLUDED IN RULE SET

The cognitive apprenticeship model was developed in tree diagram form. Each leaf on the tree represented a *goal*, which is actually a teaching action or decision. The outline below depicts the goals and how they relate to one another.

1. Provide situated instruction
    - 1.1 Select type of knowledge
        - 1.1.1 Domain knowledge
        - 1.1.2 Strategy instruction
            - 1.1.2.1 Encoding strategies
            - 1.1.2.2 Monitoring strategies
            - 1.1.2.3 Affective strategies
    - 1.2 Select method of presentation
        - 1.2.1 Model information
        - 1.2.2 Tell information
    - 1.3 Select components of presentation
        - 1.3.1 Instructional objective
        - 1.3.2 Advance organizer
        - 1.3.3 Concept map
        - 1.3.4 Mnemonic
        - 1.3.5 Learner control
    - 1.4 Select amount of scaffolding
        - 1.4.1 High
        - 1.4.2 Medium
        - 1.4.3 Low
    - 1.5 Select media components
    - 1.6 Present instruction

2. Elicit performance
    - 2.1 Select problem content
        - 2.1.1 New problem content
        - 2.1.2 Repeat/rephrase problem content
    - 2.2 Select question type
        - 2.2.1 Recall/knowledge
        - 2.2.2 Comprehension
        - 2.2.3 Application
        - 2.2.4 Analysis
        - 2.2.5 Synthesis
        - 2.2.6 Evaluation

2.3 Select type of performance
    2.3.1 Performance-based question or problem
    2.3.2 Text-based question or problem
    2.3.3 Reflection/Articulation
2.4 Present problem

3. Diagnose student response
    3.1 Collect student information

4. Provide individualized feedback
    4.1 Do not interrupt student
    4.2 Interrupt the student
        4.2.1 Select content of feedback
            4.2.1.1 Provide information about correctness/incorrectness of response
            4.2.1.2 Provide correct answer
            4.2.1.3 Provide a short explanation
            4.2.1.4 Provide praise/reinforcement
            4.2.1.5 Provide performance data
            4.2.1.6 Prompt self-review
        4.2.2 Present response
        4.2.3 Select next goal
            4.2.3.1 Go to Goal 1
            4.2.3.2 Go to Goal 2
            4.2.3.3 Next topic

APPENDIX B

INSTRUCTIONAL VARIABLES USED IN RULES

INSTRUCTIONAL VARIABLES USED IN RULES

Variable Name	Used to Represent	Possible Values	Default Values
ANS	Evaluation of student's answer to the most recently asked question	Correct, incorrect	None (varies)
ANX	Student's level of anxiety about learning	Above or below criterion	Varies. Can be determined by teacher or student input, or by testing.
AO	Whether or not an advance organizer will be used in presenting instruction at a particular point in time. Based on results from Subgoal 1.3.2.	Yes, no	Yes
APT	Student aptitude	Above or below criterion	Can be determined for each student prior to instruction based on teacher input or testing
CA	Whether or not feedback will include the correct answer to the question. Based on results from Subgoal 4.2.1.2.	Yes, no	No
CIINFO	Whether or not to provide information about the correctness or incorrectness of a response. Based on results from Subgoal 4.2.1.1.	Yes, no	No
CM	Whether or not a concept map will be used in presenting instruction at a particular point in time. Based on results from Subgoal 1.3.3.	Yes, no	No
CURRTOPIC	The student's place in the curriculum, in terms of what topic he/she is on.	*Previous topic:* topic x-1 *Current topic:* topic x *Next topic:* topic x+1	Not applicable
GOAL	The current goal	Text description of the current goal	Not applicable
HISTPERF	*Overall* student performance in the curriculum at any given point in time. This variable records how well a student has performed over a longer period of time (e.g., over several topics within the same curriculum).	Above or below criterion	Below criterion
KTYPE	Type of knowledge selected to be presented. Based on results from Subgoal 1.1 and associated leaves.	Domain, encoding, monitoring, affective	Domain
LC	Whether or not learner control will be allowed during instruction. Based on results from Subgoal 1.3.5.	Yes, no	No
LOC	Student's locus of control	Internal, external	Can be determined for each student prior to instruction based on teacher input or testing.
LOCPERF	Student performance on the most recent series of questions	Above or below criterion	Below criterion
METHOD	Method of presentation to be used. Based on results from Subgoal 1.2 and associated leaves.	Model, tell	Model
MN	Whether or not a mnemonic will be used in presenting instruction at a particular point in time. Based on results from Subgoal 1.3.4.	Yes, no	No
MOTIVLEARN	General motivation to learn (trait motivation)	Above or below criterion	Can be determined for each student prior to instruction based on teacher input or testing.
MOTIVTOPIC	Motivation to learn a particular topic (state motivation)	Above or below criterion	Can be determined for each student prior to instruction based on teacher input or testing.
NUMQUEST	Number of questions asked so far	Numerical value	None
OBJ	Whether or not an instructional objective will be used in presenting instruction at a particular point in time. Based on result from Subgoal 1.3.1.	Yes, no	Yes
PD	Whether or not to provide performance data. Based on result from Subgoal 4.2.1.5.	Yes, no	No

INSTRUCTIONAL VARIABLES USED IN RULES (CONT.)

Variable Name	Used to Represent	Possible Values	Default Values
PE	Whether or not to provide an explanation. Based on result from Subgoal 4.2.1.3.	Yes, no	No
PERFDIFF	Level of difficulty of performance	Easy, intermediate, difficult	Varies. Can be determined for each problem either by the designer or by some computer algorithm.
PERFSTATE	Whether or not a student is still working on a problem at a the time (i.e., whether he/she is done with it, or is still working on it).	Still working, done	Done
PR	Whether or not to provide reinforcement. Based on result from Subgoal 4.2.1.4.	Yes, no	No
PTYPE	The type of performance that will be required from the student. Based on results from Subgoal 2.3 and associated leaves.	Performance-based, text-based, reflection/articulation	Performance-based
PTYPEPREV	The PTYPE of the last question (i.e., most recent) asked.	Performance-based, text-based, reflection/articulation	Varies
QCONTENT	Whether the content of a problem will be new or the same as a previous problem	New, same	New
QTYPE	Type of question the student will be asked. Based on results from Subgoal 2.2 and associated leaves.	Recall/knowledge, comprehension, application, analysis, synthesis, evaluation	Recall/knowledge
QTYPEPREV	The QTYPE of the last question (i.e., most recent) asked.	Recall/knowledge, comprehension, application, analysis, synthesis, evaluation	Varies
REQAO	Whether or not the learner requests an advance organizer. Based on results from Subgoal 1.3.2.	Yes, no	No
REQCM	Whether or not the learner requests a concept map. Based on results from Subgoal 1.3.3.	Yes, no	No
REQMN	Whether or not the learner requests a mnemonic. Based on results from Subgoal 1.3.4.	Yes, no	No
REQMODEL	Whether or not the learner requests a demonstration of process or skill.	Yes, no	No
REQOBJ	Whether or not the learner requests an instructional objective	Yes, no	No
REQREPEAT	Whether or not student has requested that a question be repeated	Yes, no	No
REQREVIEW	Whether or not student has requested a review	Yes, no	No
RESPCERT	Student response certitude for the most recent question	Above or below criterion	Varies. Determined by asking students how certain they are of their responses.
RESPCERT(*topic x*)	Student's average response certitude on topic so far	Above or below criterion	Varies. Determined by students' average response certitude after answering several questions.
SCAFF	Amount of scaffolding that will need to be provided during instruction. Based on results from Subgoal 1.4 and associated leaves.	High, medium, low	High
SES	Student socioeconomic status	Above or below criterion	Can be determined for each student prior to instruction based on teacher input or testing
SR	Whether or not to prompt a self-review. Based on result from Subgoal 4.2.1.6.	Yes, no	No
SRECALL	Student performance on questions requiring recall of information	Above or below criterion	Criterion.
TESTPERF(*topic x*)	Student performance on final test for mastery of topic x	Above or below criterion	Varies, depending on student performance.

INSTRUCTIONAL VARIABLES USED IN RULES (CONT.)

Variable Name	Used to Represent	Possible Values	Default Values
TIMELEFT	Amount of time left in class or session	Above or below criterion	None (varies)
TIMEWAITING	Amount of time spent waiting for input from student (while eliciting performance)	Above or below criterion	None (varies)
TOPICCHAR(3) (1) = requires memorization of new terms or concepts (2) = can be demonstrated or modelled (e.g., a process, skill, or procedure) (3) = includes inter-related concepts	Characteristics of topic. This is an array variable. Each element of the array represents the presence or absence of one aspect of the topic. A topic can be characterized by a combination of yes and no answers for each element.	Each element may assume one of two values--either yes or no. E.g., *TOPICCHAR(1) = yes* means that the topic requires memorization *TOPICCHAR(3) = no* means that the topic does not include inter-related concepts	This information would need to be specified for each topic within the curriculum during the instructional design process, and loaded in each time the student changes to a different topic.
TOPICPERF(*topic x*)	Student's level of mastery of a topic at any given time. This variable expresses the idea ofhow quickly the student is catching on	Little or no progression, normal progression, mastery	Little or no progression
TOPICPERFCHAR(6) (1) = recall (2) = comprehension (3) = application (4) = analysis (5) = synthesis (6) = evaluation	Characteristics of the types of performance required by a topic. Each element of the array represents the presence or absence of a type of performance. A topic can be characterized by a combination of yes and no answers for each element.	Each element may assume one of two values--either yes or no. E.g., *TOPICPERFCHAR(2) = yes* means that *comprehension* needs to be assessed when eliciting performance with the student.	This information would need to be specified for each topic within the curriculum during the instructional design process, and loaded in each time the student changes to a different topic.
TOPICPROGRESS	Degree to which topic has been covered thus far This variable expresses the idea of how much of the topic material has been covered so far and how much is left.	Beginning, early, midway, nearly complete, complete	Beginning
TRIES	Number of tries a student has been given to answer the current question.	Above criterion, below criterion	Zero.

APPENDIX C

SAMPLE RULE SET

Notes on the Sample Rule Set

The purpose of the sample rule set is to illustrate how rules might be written to execute effective teaching behaviors within a cognitive apprenticeship instructional approach. The emphasis is on demonstrating how the effective teaching behavior knowledge identified in this study could be expressed in rule form. The emphasis is <u>not</u> on developing a comprehensive or executable rule set. For example, to be implemented within an instructional module, "house cleaning rules" would need to be added to keep the program from falling into infinite loops.

In developing these rules, the following assumptions were made about the context in which they would be used:

- A curriculum, consisting of a list of topics, has already been defined. The rule set teaches one topic from this curriculum until it is mastered, then moves to the next topic.

- Certain information is readily available, such as background knowledge about the student and knowledge about the nature of the subject to be taught. In an actual implementation of an intelligent tutoring system, this knowledge would need to specified for the system before students ever log on.

- Information will be collected and updated as needed in the course of a teaching session. Although this rule set makes frequent references to what values variables need to have before an action can take place, it makes minimal provision for housekeeping--i.e., for initializing those variables or updating them to reflect changes in student performance, progress within a topic, and so on. In an actual intelligent tutoring system, programmers would need to specify how and when information will be collected and updated.

- Decisions about matters such as screen design, reading level, instructional media, and how a topic will be presented, are for the most part left to the teacher or instructional designer. This set of rules only provides a generic framework which suggests what teaching actions should take place, and in what order. More specific teaching decisions can only be made when trying to design a system for a particular application.

- A mastery approach to instruction is desired. That is, a student will be taught until his or her performance exceeds a specified criterion.

- Criterion values for variables have been defined. In many cases, this rule set makes decisions based on whether the values of certain variables are *above* or *below criterion*. In an actual implementation, the range of possible values for these variables would need to be defined, and criterion values would need to be specified.

Rules for Providing Situated Instruction (Goal 1)

Goal 1: Provide situated instruction

Function: This goal (and its sub-goals) is fired to present instruction. It addresses the information presentation aspects of instruction--when the student is told or shown something. The amount presented depends on the "grain size" of the instruction. It can be very minimal - e.g., giving instructions on how to use an instructional game or simulation. Or, it can be more detailed and complex - e.g., having the student watch a video or read a long explanation.

Reasons for Goal Selection:

1) If the student is beginning a new topic.
   Example rule:

   IF *TOPICPROGRESS = beginning*
   THEN *GOAL = provide situated instruction [1]*
   TOPICPROGRESS = early

   Explanation: This rule makes Goal 1 the current goal, and sets the value of the variable TOPICPROGRESS to "early" to reflect that instruction on that topic has already begun.

2) If the student needs a fresh presentation of the current topic (or if student needs to learn a new sub-topic within the same topic) and there is time left.
   Example rule:

   IF *GOAL = reset variables to return to goal 1 [4.2.3.1]*
   TOPICPROGRESS = early OR midway OR nearly complete
   TIMELEFT > criterion
   THEN *GOAL = provide situated instruction [1]*

   Explanation: This rule assumes that the student has already completed one cycle of instruction (i.e., from Goal 1 through Goal 4) and has reached Subgoal 4.2.3.1, which means that the student should pass through another cycle on the same topic. If TOPICPROGRESS is still continuing, and there is time left, then Goal 1 becomes the current goal.

Outcome: A decision to provide situated instruction.

Next Step: Establish parameters for type of knowledge to be taught (Subgoal 1.1), method of presentation (Subgoal 1.2), components of presentation (1.3), amount of scaffolding (1.4), and delivery medium (1.5). Present instruction based on parameters (1.6).

Subgoal 1.1: Select type of knowledge

Function: This goal is fired to determine whether domain knowledge or learning strategies knowledge should be presented.

Reason for Goal Selection:

1) If Goal 1 is the current goal.
   Example rule:

   IF *GOAL = provide situated instruction [1]*
   THEN *GOAL = select type of knowledge [1.1]*

   Explanation: If the current goal is Goal 1, then the current goal should become Subgoal 1.1.

Outcome: A decision to select what type of knowledge to teach.

Next Step: Either 1.1.1 (domain knowledge) or 1.1.2 (learning strategies).

Subgoal 1.1.1: Select domain knowledge

Function: This goal is fired to select domain knowledge instruction.

Reasons for Goal Selection:

1) When a new topic is first being presented.
   Example rule:

   IF *GOAL = select type of knowledge [1.1]*
   TOPICPROGRESS = early
   THEN *GOAL = select domain knowledge [1.1.1]*

2) If a student is making satisfactory progress on a topic (as evidenced by student historical performance).
   Example rule:

   IF *GOAL = select type of knowledge [1.1]*
   TOPICPROGRESS = midway OR nearly complete
   HISTPERF > criterion
   THEN *GOAL = select domain knowledge [1.1.1]*

Outcome: A decision to teach domain knowledge.

Execution: Another rule is needed to set the knowledge type parameter (KTYPE) to "domain knowledge." For example,

IF *GOAL = select domain knowledge [1.1.1]*
THEN *KTYPE = domain*

Next Step: Select method of presentation (Subgoal 1.2).

Subgoal 1.1.2: Select strategy instruction

Function: This goal to select instruction on learning strategies, such as encoding strategies, comprehension monitoring strategies, or affective strategies.

Reason for Goal Selection:

1) The student has not been performing very well on questions related to the topic.
   Example Rule:

IF	*GOAL = select type of knowledge [1.1]*
	TOPICPROGRESS = midway OR nearly complete
	HISTPERF < criterion
THEN	*GOAL = select strategy instruction [1.1.2]*

Outcome: A decision to teach learning strategies.

Next step: Decide what type of learning strategies to teach (Subgoal 1.1.2.1, 1.1.2.2, or 1.1.2.3).

Subgoal 1.1.2.1: Teach encoding strategies

Function: This goal is fired to teach the student strategies for remembering information better.

Reasons for Goal Selection:

1) If (a) the goal is to provide strategy instruction, (b) the topic is one that requires memorization, and (c) the student has not been performing well on items requiring recall of information.
Example rule:

IF *GOAL = provide strategy instruction [1.1.2]*
TOPICCHAR(1) = yes (i.e., topic requires memorization)
SRECALL < criterion
THEN *GOAL = teach encoding strategies [1.1.2.1]*

2) If (a) the goal is to provide strategy instruction, and (b) there is no specific reason to choose one strategy over another.
Example rule:

IF *GOAL = provide strategy instruction [1.1.2]*
GOAL {1.1.2.1, 1.1.2.2, or 1.1.2.3} not selected
THEN *GOAL = teach encoding strategies [1.1.2.1]*

Outcome: A decision to teach encoding strategies.

Execution: Another rule is needed to set the Knowledge Type parameter to "encoding strategies." For example,

IF *GOAL = teach encoding strategies [1.1.2.1]*
THEN *KTYPE = encoding*

Next step: Select method of presentation (Subgoal 1.2).

Subgoal 1.1.2.2: Teach monitoring strategies

Function: This goal is fired to teach the student to recognize when he or she is not understanding.

Reason for Goal Selection:

1) If the student is not performing well on a topic, but thinks that he/she is (as indicated by his/her response certitude).
   Example rule:

   IF *GOAL = provide strategy instruction [1.1.2]*
   TOPICPERF(topic x) = little or no progression
   RESPCERT > criterion
   THEN *GOAL = teach monitoring strategies [1.1.2.2]*

Outcome: A decision to teach monitoring strategies.

Execution: Another rule is needed to set the Knowledge Type parameter to "monitoring strategies." For example,

IF *GOAL = teach monitoring strategies [1.1.2.2]*
THEN *KTYPE = monitoring*

From here, you should go to Subgoal 1.2. (The rule to do so is specified under Subgoal 1.2).

Subgoal 1.1.2.3: Teach affective strategies

Function: This goal is fired to teach students strategies for dealing with debilitating emotions, such as test anxiety.

Reasons for Goal Selection:

1) If it is known that the student is highly anxious.
Example rule:

IF	*GOAL = provide strategy instruction [1.1.2]*
	ANX > criterion
THEN	*GOAL = teach affective strategies [1.1.2.3]*

2) If the student seems to know the topic (based on informal performance measures) but does poorly on tests.
Example rule:

IF	*GOAL = provide strategy instruction [1.1.2]*
	TOPICPERF(topic x) > criterion
	TESTPERF(topic x) < criterion
THEN	*GOAL = teach affective strategies [1.1.2.3]*

3) If the student lacks motivation to learn a particular topic (state motivation).
Example rule:

IF	*GOAL = provide strategy instruction [1.1.2]*
	MOTIVTOPIC < criterion
THEN	*GOAL = teach affective strategies [1.1.2.3]*

4) If the student lacks motivation to learn in general (trait motivation).
Example rule:

IF	*GOAL = provide strategy instruction [1.1.2]*
	MOTIVLEARN < criterion
THEN	*GOAL = teach affective strategies [1.1.2.3]*

Outcome: A decision to teach affective strategies.

Execution: A rule is needed to set the Knowledge Type variable to "affective strategies." For example,

IF	*GOAL = teach affective strategies [1.1.2.3]*
THEN	*KTYPE = affective*

Next Step: Select method of presentation (Subgoal 1.2).

Subgoal 1.2: Select method of presentation

Function: This goal is fired to decide whether to model or to tell information.

Reasons for Goal Selection:

1) If the Knowledge Type parameter has been set.
   Example rule:

   IF $\quad$ *KTYPE ≠ 0*
   THEN $\quad$ *GOAL = select method of presentation [1.2]*

Outcome: Decision to select method of presentation.

Next step: Decide whether to model knowledge (Subgoal 1.2.1) or to tell knowledge (Subgoal 1.2.2).

Subgoal 1.2.1: Model knowledge

Function: This goal is fired to model knowledge (i.e., teach by showing or demonstrating).

Reasons for Goal Selection:

1) If instruction is just beginning and if the topic lends itself to being demonstrated or modeled.
   Example rule:

   IF *GOAL = select method of presentation [1.2]*
   TOPICPROGRESS = early
   TOPICCHAR(2) = yes (i.e., topic can be demonstrated or modeled)
   THEN *GOAL = model knowledge [1.2.1]*

2) If the student requests a model.
   Example rule:

   IF *GOAL = select method of presentation [1.2]*
   TOPICPROGRESS = continuing
   TOPICCHAR(2) = yes (i.e., topic can be demonstrated or modeled)
   HISTPERF > criterion
   REQMODEL = yes
   THEN *GOAL = model knowledge [1.2.1]*

Outcome: A decision to present instruction using a modeling approach.

Execution: Another rule is needed to set the Teaching Method parameter (METHOD) to "model." For example,

IF *GOAL = model knowledge [1.2.1]*
THEN *METHOD = model*

Next Step: Select components of instructional presentation (Subgoal 1.3).

Subgoal 1.2.2: Tell knowledge

Function: This goal is fired to tell knowledge.

Reasons for Goal Selection:

1) If the topic requires memorization of terms or concepts.
   Example rule:

   IF *GOAL = select method of presentation [1.2]*
   TOPICPROGRESS = continuing
   TOPICCHAR(1) = yes (i.e., topic requires memorization of new terms or concepts)
   THEN *GOAL = tell knowledge [1.2.2]*

2) If the student has historically performed well on this topic and requests a review of the material.
   Example rule:

   IF *GOAL = select method of presentation [1.2]*
   TOPICPROGRESS= beginning
   TOPICCHAR(1) = yes (i.e., topic requires memorization of new terms or concepts)
   HISTPERF > criterion
   REQREVIEW = yes
   THEN *GOAL = tell knowledge [1.2.2]*

Outcome: A decision to present information to the student by telling the student.

Execution: Another rule is needed to set the Method of Presentation (METHOD) parameter to "tell." For example,

IF *GOAL = tell knowledge*
THEN *METHOD = tell*

Next Step: Select components of instructional presentation (Subgoal 1.3).

Subgoal 1.3: Select components of instructional presentation

Function: This goal is fired to select which components should be included in an instructional presentation--e.g., instructional objective, advance organizer, concept map, etc.

Reasons for Goal Selection:

1) If Method of Presentation has been selected
   Example Rule:

   IF *METHOD* $\neq$ *0*
   THEN *GOAL = select components of instructional presentation [1.3]*

Outcome: A decision to select components of instructional presentation.

Next step: Select components to include, such as instructional objectives (Subgoal 1.3.1), advance organizers (Subgoal 1.3.2), concept maps (Subgoal 1.3.3), mnemonics (Subgoal 1.3.4), and learner control (Subgoal 1.3.5).

Subgoal 1.3.1: Provide an instructional objective

Function: This goal is fired to provide an instructional objective.

Reasons for Goal Selection:

1) If just beginning presentation of a topic
   Example Rule:

   IF *GOAL = select components of instructional presentation*
   TOPICPROGRESS = early
   THEN *GOAL = provide instructional objective [1.3.1]*

2) If beginning a new sub-topic within a topic
   Example Rule:

   IF *GOAL = select components of instructional presentation [1.3]*
   TOPICPROGRESS = midway OR nearly complete
   THEN *GOAL = provide instructional objective (proximal) [1.3.1]*

3) If the student asks to see the objective
   Example Rule:

   IF *REQOBJ = yes*
   THEN *GOAL = provide instructional objective*

Outcome: A decision to present an objective.

Execution: Another rule is needed to set the Present Objective (OBJ) parameter to "yes." For example,

IF *GOAL = provide instructional objective*
THEN *OBJ = yes*

Next Step: See if any other components should be selected (Subgoals 1.3.2, 1.3.3, 1.3.4, 1.3.5) or select amount of scaffolding (Subgoal 1.4).

Subgoal 1.3.2: Provide an advance organizer

Function: This goal is fired to provide an advance organizer.

Reasons for Goal Selection:

1) When a new topic is first presented:
   Example Rule:

   IF *GOAL = select components of instructional presentation [1.3]*
   TOPICPROGRESS = early
   THEN *GOAL = provide an advance organizer [1.3.2]*

2) If the student requests an advance organizer:
   Example Rule:

   IF *GOAL = select components of instructional presentation [1.3]*
   REQAO = yes
   THEN *GOAL = provide an advance organizer [1.3.2]*

Outcome: A decision to present an advanced organizer.

Execution: Another rule is needed to set the Advanced Organizer (AO) parameter to "yes." For example,

IF *GOAL = provide an advance organizer [1.3.2]*
THEN *AO = yes*

Next Step: See if any other components should be selected (Subgoals 1.3.2, 1.3.3, 1.3.4, 1.3.5) or select amount of scaffolding (Subgoal 1.4).

Subgoal 1.3.3: Provide a concept map

Function: This goal is fired to provide a concept map.

Reasons for Goal Selection:

1) If student is just beginning a new topic and that topic lends itself to concept mapping.
   Example Rule:

IF	*GOAL = select components of instructional presentation [1.3]*
	TOPICPROGRESS = beginning
	TOPICCHAR(3) = yes (i.e., topic includes inter-related concepts)
THEN	*GOAL = provide concept map [1.3.3]*

2) If the student requests a concept map, and the topic lends itself to concept mapping.
   Example Rule:

IF	*GOAL = select components of instructional presentation [1.3]*
	TOPICCHAR(3) = yes (i.e., topic includes inter-related concepts)
	REQCM = yes
THEN	*GOAL = provide a concept map [1.3.3]*

Outcome: A decision to provide a concept map.

Execution: An additional rule is needed to set the Concept Map (CM) parameter to "yes." For example,

IF	*GOAL = provide a concept map [1.3.3]*
THEN	*CM = yes*

Next Step: See if any other components should be selected (Subgoals 1.3.2, 1.3.3, 1.3.4, 1.3.5) or select amount of scaffolding (Subgoal 1.4).

Subgoal 1.3.4: Provide a mnemonic

Function: This goal is fired to provide a mnemonic.

Reasons for Goal Selection:

1) If the topic requires memorization of new terms or concepts.
Example Rule:

IF *GOAL = select components of instructional presentation [1.3]*
TOPICCHAR(1) = yes (i.e., topic requires memorization of new terms or concepts)
THEN *GOAL = provide a mnemonic [1.3.4]*

2) If the student requests a mnemonic.
Example Rule:

IF *GOAL = select components of instructional presentation [1.3]*
REQMN = yes
THEN *GOAL = provide a mnemonic [1.3.4]*

Outcome: A decision to provide a mnemonic.

Execution: Another rule is needed to set the Mnemonic parameter (MN) to "yes." For example,

IF *GOAL = provide a mnemonic [1.3.4]*
THEN *MN = yes*

Next Step: See if any other components should be selected (Subgoals 1.3.2, 1.3.3, 1.3.4, 1.3.5) or select amount of scaffolding (Subgoal 1.4).

Subgoal 1.3.5: Allow learner control

Function: This goal is fired to allow learner control.

Reasons for Goal Selection:

1) If the student is a high aptitude learner.
Example rule:

IF *GOAL = select components of instructional presentation [1.3]*
TOPICPROGRESS = early OR midway OR nearly complete
APT > criterion
THEN *GOAL = allow learner control of some features of instruction [1.3.5]*

Outcome: A decision to allow learner control.

Execution: Another rule is needed, to set the Learner Control (LC) parameter to "yes." For example,

IF *GOAL = allow learner control of some features of instruction [1.3.5]*
THEN *LC = yes*

Next Step: See if any other components should be selected (Subgoals 1.3.2, 1.3.3, 1.3.4, 1.3.5) or select amount of scaffolding (Subgoal 1.4).

Subgoal 1.4: Select amount of scaffolding

Function: This goal is fired to select the amount of scaffolding (high, medium, or low) to provide.

Reasons for Goal Selection:

1) If all available components of an instructional presentation have already been considered (but not necessarily selected).
   Example rule:

   IF GOAL = select the components of instructional presentation [1.3]
   THEN GOAL = select the amount of scaffolding [1.4]

Outcome: A decision to select the amount of scaffolding to provide.

Next step: Decide whether to provide high (1.4.1), medium (1.4.2), or low (1.4.3) scaffolding.

Subgoal 1.4.1: Select high scaffolding value

Function: This goal is fired to provide high scaffolding.

Reasons for Goal Selection:

1) If the student has made little progress through the topic.
   Example rule:

   IF GOAL = select amount of scaffolding [1.4]
   TOPICPERF(topic x) = little or no progress
   THEN GOAL = select high scaffolding value [1.4]

Outcome: A decision to provide high scaffolding.

Execution: A rule is needed to set the Scaffolding (SCAFF) parameter to "high." For example,

IF GOAL = select high scaffolding value [1.4.1]
THEN SCAFF = high

Next step: Select media components (Subgoal 1.5).

Subgoal 1.4.2: Select medium scaffolding value

Function: This goal is fired to provide medium scaffolding.

Reasons for Goal Selection:

1) If the student is midway through the topic and is progressing at a normal rate of speed. Example rule:

IF	*GOAL = select amount of scaffolding [1.4]*
	TOPICPERF(topic x) = normal progression
THEN	*GOAL = select medium scaffolding value [1.4]*

Outcome: A decision to provide a medium level of scaffolding.

Execution: Another rule is needed to set the Scaffolding (SCAFF) parameter to "medium." For example,

IF	*GOAL = select medium scaffolding value [1.4.2]*
THEN	*SCAFF = medium*

Next step: Select media components (Subgoal 1.5).

Subgoal 1.4.3: Select low scaffolding value

Function: This goal is fired to provide low scaffolding.

Reason for Goal Selection:

1) Student has nearly mastered a topic.
   Example rule:

   IF *GOAL = select amount of scaffolding [1.4]*
   TOPICPERF(topic x) = mastery
   THEN *GOAL = select low scaffolding value [1.4. 3]*

Outcome: Decision to provide a low level of scaffolding.

Execution: Another rule is needed to set the Scaffolding (SCAFF) parameter to "low." For example,

IF *GOAL = select low scaffolding value [1.4.3]*
THEN *SCAFF = low*

Next step: Select media components (Subgoal 1.5).

Subgoal 1.5: Select media components

Function: This goal is fired to select media components.

Reasons for Goal Selection:

1) If amount of scaffolding has been selected,
   Example rule:

   IF *SCAFF* $\neq$ *0*
   THEN *GOAL = select media components [1.5]*

Outcome: A decision to select media components.

Execution: A set of rules for selecting appropriate instructional media (e.g., text, video, animation, graphics, audio, etc.) needs to be inserted here. An example rule for accessing this set follows.

IF *GOAL = select media components*
THEN *GOAL = select appropriate instructional media*

Next step: Present instruction (Subgoal 1.6)

Subgoal 1.6: Present situated instruction

Function: This goal is fired to present situated instruction according to the parameters established by the previous sub-goals.

Reasons for Goal Selection:

1) If instructional media have already been selected.
   Example rule:

   IF *instructional media have been selected*
   THEN *provide situated instruction within parameters specified by KTYPE, METHOD, OBJ, AO, CM, MN, LC, SCAFF, and media components*

Outcome: Instruction presented according to established parameters.

Execution: Some mechanism for using these parameters to decide how to present instruction needs to be developed.

Next step: Test student knowledge by eliciting student performance (Goal 2).

Rules for Eliciting Performance (Goal 2)

Goal 2: Elicit performance

Function: This goal (and its associated sub-goals) is fired when there is a need to elicit performance from the student. The purpose of eliciting performance may be either to test or to give the student an opportunity to learn by doing.

Reasons for Goal Selection:

1) If situated instruction has been provided.
   Example rule:

   IF *situated instruction has been provided*
   THEN *GOAL = elicit performance [2]*

2) If the student needs more practice to master a topic.
   Example rule:

   IF *GOAL = reset variables to return to Goal 1 [4.2.3.2]*
   TIMELEFT > criterion
   TOPICPROGRESS = early OR midway OR nearly complete
   THEN *GOAL = elicit performance [2]*

Outcome: A decision to elicit student performance.

Next step: Select problem content (Subgoal 2.1), question type (Subgoal 2.2), and performance type (Subgoal 2.3). Present problem (Subgoal 2.4).

Subgoal 2.1: Select problem content

Function: This goal is fired to select whether the content of a question or problem should be new or old.

Reasons for Goal Selection:

1) If current goal is to elicit performance.
   Example rule:

   IF *GOAL = elicit performance*
   THEN *GOAL = select problem content [2.1]*

Outcome: A decision to select problem content.

Next step: Decide whether to present a new problem (Subgoal 2.1.1.) or to re-present/rephrase a previous problem (Subgoal 2.1.2).

Subgoal 2.1.1: New problem content

Function: This goal is fired to select new problem content.

Reasons for Goal Selection:

1) If the student answered the last problem correctly and has performed satisfactorily on the last few problems on a topic.
   Example rule:

   IF *GOAL = select problem content [2.1]*
   ANS = correct
   LOCPERF > criterion
   TOPICPERF(topic x) = normal progression
   THEN *GOAL = new problem content [2.1.1]*

Outcome: A decision to present new problem content.

Execution: Another rule is needed to set the problem content (QCONTENT) parameter to "new." For example,

IF *GOAL = new problem content [2.1.1]*
THEN *QCONTENT = new*

Next step: Select question type (Subgoal 2.2).

Subgoal 2.1.2: Repeat/rephrase problem content

Function: This goal is fired to repeat or rephrase problem content.

Reasons for Goal Selection:

1) If the student answered the last problem incorrectly.
   Example rule

   IF *GOAL = select problem content [2.1]*
   ANS = incorrect
   LOCPERF > criterion
   TOPICPERF(topic x) = normal progression
   THEN *GOAL = repeat/rephrase problem content [2.1.2]*

2) If the student requests a review of the previous problem.
   Example rule:

   If *GOAL = select problem content [2.1]*
   REQREPEAT = yes
   THEN *GOAL = repeat/rephrase problem content [2.1.2]*

Outcome: A decision to repeat or rephrase a problem.

Execution: Another rule is needed to set the Content (QCONTENT) parameter to "same." For example,

IF *GOAL = repeat/rephrase problem content [2.1.2]*
THEN *QCONTENT = same*

Next step: Select question type (Subgoal 2.2).

Subgoal 2.2: Select question type

Function: This goal is fired to select what type of question to ask (e.g., recall/knowledge, comprehension, application, analysis, synthesis, or evaluation).

Reasons for Goal Selection:

1) If problem content has been selected.
   Example rule:

   IF *QCONTENT* $\neq$ *0*
   THEN *GOAL = select question type [2.2]*

Outcome: A decision to select the type of question to ask.

Next step: Select one of the following question types - Recall/knowledge (Subgoal 2.2.1), Comprehension (2.2.2), Application (2.2.3), Analysis (2.2.4), Synthesis (2.2.5), or Evaluation (2.2.6).

Subgoal 2.2.1: Recall/knowledge

Function: This goal is fired to ask a recall/knowledge question.

Reasons for Goal Selection:

1) If the previous question type was recall/knowledge and the question content is the same.
Example rule:

IF	*GOAL = select question type [2.2]*
	QTYPEPREV = recall/knowledge
	QCONTENT = same
THEN	*GOAL = recall/knowledge [2.2.1]*

2) If the student is just beginning the topic and performing the topic requires recall.
Example rule:

IF	*GOAL = select question type [2.2]*
	TOPICPROGRESS = beginning
	TOPICPERFCHAR(1) = yes (i.e., topic performance includes recall)
THEN	*GOAL = recall/knowledge [2.2.1]*

Outcome: A decision to ask a recall/knowledge question.

Execution: Another rule is needed to set the Question Type (QTYPE) parameter to "recall/knowledge." For example,

IF	*GOAL = recall/knowledge [2.2.1]*
THEN	*QTYPE = recall/knowledge*

Next step: Select type of performance (Subgoal 2.3).

Subgoal 2.2.2: Comprehension

Function: This goal is fired to ask a comprehension question.

Reasons for Goal Selection:

1) If the previous question was a comprehension question and the content is the same.
   Example rule:

   IF *GOAL = select question type [2.2]*
   QTYPEPREV = comprehension
   QCONTENT = same
   THEN *GOAL = comprehension [2.2.2]*

2) If the previous question was a recall/knowledge question and the content is new.
   Example rule:

   IF *GOAL = select question type [2.2]*
   QTYPEPREV = recall/knowledge
   QCONTENT = new
   THEN *GOAL = comprehension [2.2.2]*

Outcome: A decision to ask a comprehension question.

Execution: Another rule is needed to set the Question Type (QTYPE) parameter to "comprehension." For example,

IF *GOAL = comprehension [2.2.2]*
THEN *QTYPE = comprehension*

Next step: Select type of performance (Subgoal 2.3).

Subgoal 2.2.3: Application

Function: This goal is fired to ask an application question.

Reasons for Goal Selection:

1) If the previous question was an application question, and the content is the same. Example rule:

   IF GOAL = select question type [2.2]
   QTYPEPREV = application
   QCONTENT = same
   THEN GOAL = application [2.2.3]

2) If the previous question was a comprehension question, and the content is new. Example rule:

   IF GOAL = select question type [2.2]
   QTYPEPREV = comprehension
   QCONTENT = new
   THEN GOAL = application [2.2.3]

Outcome: A decision to ask an application question.

Execution: Another rule is needed to set the QTYPE parameter to "application." For example,

IF GOAL = application [2.2.3]
THEN QTYPE = application

Next step: Select type of performance (Subgoal 2.3).

Subgoal 2.2.4: Analysis

Function: This goal is fired to ask an analysis question.

Reasons for Goal Selection:

1) If the previous question was an analysis question, and the content is the same.
   Example rule:

   IF *GOAL = select question type [2.2]*
   QTYPEPREV = analysis
   QCONTENT = same
   THEN *GOAL = analysis [2.2.4]*

2) If the previous question was an application question, and the content is new.
   Example rule:

   IF *GOAL = select question type [2.2]*
   QTYPEPREV = application
   QCONTENT = new
   THEN *GOAL = analysis [2.2.4]*

Outcome: A decision to ask an analysis question.

Execution: Another rule is needed to set the QTYPE parameter to "analysis." For example,

IF *GOAL = analysis [2.2.4]*
THEN *QTYPE = analysis*

Next step: Select type of performance (Subgoal 2.3).

Subgoal 2.2.5: Synthesis

Function: This goal is fired to ask a synthesis question.

Reasons for Goal Selection:

1) If the previous question was a synthesis question, and the content is the same.
Example rule:

IF *GOAL = select question type [2.2]*
QTYPEPREV = synthesis
QCONTENT = same
THEN *GOAL = synthesis [2.2.5]*

2) If the previous question was an analysis question, and the content is new.
Example rule:

IF *GOAL = select question type [2.2]*
QTYPEPREV = analysis
QCONTENT = new
THEN *GOAL = synthesis [2.2.5]*

Outcome: A decision to ask a synthesis question.

Execution: Another rule is needed to set the QTYPE parameter to "synthesis." For example,

IF *GOAL = synthesis [2.2.5]*
THEN *QTYPE = synthesis*

Next step: Select type of performance (Subgoal 2.3).

Subgoal 2.2.6: Evaluation

Function: This goal is fired to ask an evaluation question.

Reasons for Goal Selection:

1) If the previous question was an evaluation question, and the content is the same.
   Example rule:

   IF *GOAL = select question type [2.2]*
   QTYPEPREV = evaluation
   QCONTENT = same
   THEN *GOAL = evaluation [2.2.6]*

2) If the previous question was a synthesis question, and the content is new.
   Example rule:

   IF *GOAL = select question type [2.2]*
   QTYPEPREV = synthesis
   QCONTENT = new
   THEN *GOAL = evaluation [2.2.6]*

Outcome: A decision to ask an evaluation question.

Execution: Another rule is needed to set the QTYPE parameter to "evaluation." For example,

IF *GOAL = evaluation [2.2.6]*
THEN *QTYPE = evaluation*

Next step: Select type of performance (Subgoal 2.3).

Subgoal 2.3: Select type of performance

Function: This goal is fired to select the type of performance to require--e.g., performance-based, text-based, or reflection/articulation.

Reasons for Goal Selection:

1) If the question type has been selected.

IF $\quad$ *QTYPE* $\neq 0$
THEN $\quad$ *GOAL = select type of performance [2.3]*

Outcome: A decision to select the type of performance required of the student.

Next step: Select one of the following - performance-based question/problem (Subgoal 2.3.1), text-based question/problem (2.3.2), or reflection and articulation (2.3.3).

Subgoal 2.3.1: Performance based question or problem

Function: This goal is fired to select a performance-based question or problem (e.g., a simulation).

Reasons for Goal Selection:

1) If the previous problem was performance-based, and the content is the same,
Example rule:

IF GOAL = Select type of performance [2.3]
QCONTENT = same
PTYPEPREV = simulation
THEN GOAL = performance based question or problem [2.3.1]

2) If the teaching method used was modeling, and the student is making normal progress through the topic.
Example rule:

IF GOAL = select type of performance [2.3]
METHOD = model
TOPICPERF(topic x) = normal progression
THEN GOAL = performance-based question or problem [2.3.1]

3) If the student lacks motivation, but has been performing well on the topic.
Example rule:

IF GOAL = select type of performance [2.3]
MOTIVLEARN < criterion
LOCPERF > criterion
THEN GOAL = performance-based question or problem [2.3.1]

Outcome: A decision to use a performance-based question or problem to assess the student's understanding of the topic.

Execution: Another rule is needed to set the Performance Type (PTYPE) parameter to "performance." For example,

IF GOAL = performance-based question or problem [2.3.1]
THEN PTYPE = performance

Next step: Present the problem (Subgoal 2.4).

Subgoal 2.3.2: Text-based question or problem

Function: This goal is fired to present a text-based question or problem (e.g., multiple choice).

Reasons for Goal Selection:

1) If the previous question was text-based, and if the content is the same.
Example rule:

IF *GOAL = select type of performance [2.3]*
QCONTENT = same
PTYPEPREV = text-based question or problem
THEN *GOAL = text-based question or problem [2.3.2]*

2) If the student is just beginning to learn a topic.
Example rule:

IF *GOAL = select type of performance [2.3]*
TOPICPROGRESS = early
THEN *GOAL = text-based question or problem [2.3.2]*

3) If the instructional presentation method involved telling.
Example rule:

IF *GOAL = select type of performance [2.3]*
METHOD = tell
THEN *GOAL = text-based question or problem [2.3.2]*

Outcome: A decision to ask a text-based question or problem.

Execution: An additional rule is needed to set the PTYPE parameter to "text-based." For example,

IF *GOAL = text-based question or problem [2.3.2]*
THEN *PTYPE = text-based question or problem*

Next step: Present the problem (Subgoal 2.4).

Subgoal 2.3.3: Reflection/Articulation

Function: This goal is fired to require the student to reflect upon or articulate cognitive processes (e.g., "what have you learned today?)

Reasons for Goal Selection:

1) If the instructional period is almost over (e.g., the end of class).
   Example rule:

   IF *GOAL = select type of performance [2.3]*
   TIMELEFT < criterion
   THEN *GOAL = reflection/articulation [2.3.5]*

2) If the student is nearly finished with the current topic.
   Example rule:

   IF *GOAL = select type of performance [2.3]*
   TOPICPROGRESS = nearly complete
   THEN *GOAL = reflection/articulation [2.3.5]*

Outcome: A decision to ask the student to reflect on/articulate thoughts about the lesson material.

Execution: An additional rule is needed to set the PTYPE parameter to "reflection." For example,

IF *GOAL = reflection [2.3.5]*
THEN *PTYPE = reflection*

Next step: Present the problem (Subgoal 2.4).

Subgoal 2.4: Present problem

Function: This goal is fired to present a question or problem to the student, based on the parameters established in the earlier goals. The question or problem may either require a single response or a series of responses (e.g., an instructional game or simulation).

Reasons for Goal Selection:

1) Performance type has already been selected.
   Example rule:

   IF $\quad$ *PTYPE* $\neq$ *0*
   THEN $\quad$ *GOAL = present problem [2.4]*

Outcome: A decision to present the question or problem.

Execution: Some mechanism for using these parameters to formulate a question or problem needs to be developed. For example,

IF $\quad$ *GOAL = present problem [2.4]*
THEN $\quad$ *present problem within parameters specified by QCONTENT, QTYPE, and PTYPE.*

Next step: Diagnose student response (Goal 3).

Rules for Diagnosis

GOAL 3: Diagnose student response

Function: This goal diagnoses the student's responses to the question/problem from Goal 2.

Reasons for Goal Selection:

1) Problem has been presented to student.
Example rule:

IF *problem has been presented*
THEN *GOAL = diagnose student response [3]*

Outcome: A decision to diagnose the student's response.

Next step: Collect student information (Subgoal 3.1).

Subgoal 3.1: Collect student information

Function: This goal collects student response data.

Reasons for Goal Selection:

1) A decision to diagnose the student's response has been made.
   Example rule:

   IF *GOAL = diagnose student response [3]*
   THEN *GOAL = collect student information [3.1]*

Outcome: A decision to collect student information.

Execution: Some mechanism is needed for accumulating and storing student data. For example,

IF *GOAL = collect student information [3.1]*
THEN *collect data such as ANS, TRIES, TIMEWAITING, and other performance data as needed.*

Next step: Provide feedback (Goal 4).

Rules for Providing Feedback

Goal 4: Provide individualized feedback.

Function: This goal provides individualized feedback at appropriate junctures, based on factors such as how long the student has taken to respond and how correct the answers have been. Feedback is defined broadly to include *not* interrupting the student as a form of feedback.

Reasons for Goal Selection:

1) If diagnosis information has been collected.
   Example rule:

   IF *(diagnosis information has been collected)*
   THEN *GOAL = provide individualized feedback [4]*

Outcome: A decision to provide some type of feedback.

Next step: Either let the student keep working on the problem (Subgoal 4.1) or interrupt the student (Subgoal 4.2).

Subgoal 4.1: Do not interrupt student

Function: This goal is fired to decide not to interrupt the student for the time being.

Reasons for Goal Selection:

1) If the student is still working on the problem, is performing adequately, but has still not mastered the topic.
Example rule:

IF *GOAL = provide individualized feedback [4]*
PERFSTATE = still working
LOCPERF > criterion
TOPICPERF (topic x) < mastery
THEN *GOAL = do not interrupt student [4.1]*

Outcome: A decision not to interrupt the student.

Execution: A rule is needed to continue diagnosis. For example,

IF *GOAL = do not interrupt student [4.1]*
THEN *GOAL = diagnose student response [3]*

Next step: Continue diagnosis (Goal 3).

Subgoal 4.2: Interrupt the student

Function: This goal is fired to interrupt the student.

Reasons for Goal Selection:

1) The student has demonstrated mastery of the topic.
Example rule:

IF	*GOAL = provide individualized feedback [4]*
	LOCPERF > criterion
	TOPICPERF (topic x) = mastery
THEN	*GOAL = interrupt the student [4.2]*

2) The student is not performing well.
Example rule:

IF	*GOAL = provide individualized feedback [4]*
	TRIES > criterion
	LOCPERF < criterion
THEN	*GOAL = interrupt the student [4.2]*

3) The student is taking too long to respond to the question.
Example rule:

IF	*GOAL = provide individualized feedback [4]*
	TIMEWAITING > criterion
THEN	*GOAL = interrupt the student [4.2]*

Outcome: A decision to interrupt the student.

Next step: Select content of feedback (4.2.1) and present feedback (

Subgoal 4.2.1: Select content of feedback

Function: This goal is fired to select the components of the feedback (e.g., whether the response was correct or incorrect, what the correct answer is, a short explanation, etc.). That is, the feedback may include any or all of these components, depending on which rules fire.

Reasons for Goal Selection:

1) A decision to interrupt the student has been made.
   Example rule:

   IF   *GOAL = interrupt the student [4.2]*
   THEN *GOAL = select content of feedback [4.2.1]*

Outcome: A decision to select the content of feedback.

Next step: Consider including each of the following components in the feedback: information about correctness/incorrectness of response (Subgoal 4.2.1.1), the correct answer (4.2.1.2), a short explanation (4.2.1.3), praise/reinforcement (4.2.1.4), performance data (4.2.1.5), and prompting self-review (4.2.1.6).

Subgoal 4.2.1.1: Provide information about correctness or incorrectness of response

Function: This goal is fired to provide information about the correctness or incorrectness of the student's response.

Reasons for Goal Selection:

1) If goal is to select content of feedback.
   Example rule:

   IF *GOAL = select content of feedback [4.2.1]*
   THEN *GOAL = provide information about correctness or incorrectness of response [4.2.1.1]*

Outcome: A decision to provide information about correctness or incorrectness of response.

Execution: Another rule is needed to set Correct/Incorrect Information (CIINFO) parameter to "yes." For example,

IF *GOAL = provide information about correctness or incorrectness of response [4.2.1.1]*
THEN *CIINFO = yes*

Next step: Consider whether or not to provide the correct answer (Subgoal 4.2.1.2).

Subgoal 4.2.1.2: Provide correct answer

Function: This goal is fired to provide the correct answer.

Reasons for Goal Selection:

1) If answer is incorrect or partially incorrect.
   Example rule:

   IF *GOAL = select content of feedback [4.2.1]*
   ANS = incorrect OR partially correct
   THEN *GOAL = provide correct answer [4.2.1.2]*

Outcome: A decision to provide correct answer information.

Execution: Another rule is needed to set the correct answer (CA) parameter to "yes." For example,

IF *GOAL = provide correct answer [4.2.1.2]*
THEN *CA = yes*

Next step: Consider whether or not to provide a explanation (Subgoal 4.2.1.3).

Subgoal 4.2.1.3: Provide a short explanation

Function: This goal is fired to provide a short explanation.

Reasons for Goal Selection:

1) If answer is incorrect or partially incorrect.
   Example rule:

   IF *GOAL = select content of feedback [4.2.1]*
   ANS = incorrect OR partially correct
   THEN *GOAL = provide a short explanation [4.2.1.3]*

Outcome: A decision to provide a short explanation.

Execution: Another rule is needed to set the Provide Explanation (PE) parameter to "yes." For example,

IF *GOAL = provide a short explanation [4.2.1.3]*
THEN *PE = yes*

Next step: Consider whether or not to provide praise/reinforcement (Subgoal 4.2.1.4).

Subgoal 4.2.1.4: Provide praise/reinforcement

Function: This goal is fired to provide praise/reinforcement.

Reasons for Goal Selection:

1) If the answer was correct, and the problem was difficult.
   Example rule:

   IF *GOAL = select content of feedback [4.2.1]*
   ANS = correct
   PERFDIFF = difficult
   THEN *GOAL = provide praise/reinforcement [4.2.1.4]*

2) If the answer was correct and the problem was of intermediate difficulty, but the student is a low aptitude student.
   Example rule:

   IF *GOAL = select content of feedback [4.2.1]*
   ANS = correct
   PERFDIFF = intermediate
   APT < criterion
   THEN *GOAL = provide praise/reinforcement [4.2.1.4]*

Outcome: A decision to provide praise/reinforcement.

Execution: Another rule is needed to set the Praise/Reinforcement (PR) parameter to "yes." For example,

IF *GOAL = provide praise/reinforcement [4.2.1.4]*
THEN *PR = yes*

Next step: Consider whether or not to provide performance data (Subgoal 4.2.1.5).

Subgoal 4.2.1.5: Provide performance data

Function: This goal is fired to provide performance data (e.g., scores, summary data).

Reasons for Goal Selection:

1) If a certain number of questions have been asked.
   Example rule:

   IF *GOAL = select content of feedback [4.2.1]*
   NUMQUEST > criterion
   THEN *GOAL = provide performance data [4.2.1.5]*

Outcome: A decision to provide performance data.

Execution: Another rule is needed to set the Performance Data (PD) parameter to "yes." For example,

   IF *GOAL = provide performance data [4.2.1.5]*
   THEN *PD = yes*

Next step: Consider whether or not to prompt the student to self-review (Subgoal 4.2.1.6).

Subgoal 4.2.1.6: Prompt self-review

Function: This goal is fired to prompt the student to review his or her response.

Reasons for Goal Selection:

1) If the student has been performing satisfactorily, but then answers a problem incorrectly. Example rule:

   IF *GOAL = select content of feedback [4.2.1]*
   ANS = incorrect OR partially correct
   TOPICPERF(topic x) = normal progression
   LOCPERF > criterion
   THEN *GOAL = prompt self-review [4.2.1.6]*

Outcome: A decision to prompt self-review.

Execution: Another rule is needed to set the Self Review (SR) parameter to "yes." For example,

IF *GOAL = prompt self-review [4.2.1.6]*
THEN *SR = yes*

Next step: Present feedback according to the parameters identified (Subgoal 4.2.2).

Subgoal 4.2.2: Present response

Function: This goal is fired to present feedback according to the parameters established in Subgoal 4.2.1.

Reasons for Goal Selection:

1) If feedback parameters have been selected.
   Example rule:

   IF *(feedback parameters have been selected)*
   THEN *GOAL = present response [4.2.2]*

Outcome: A decision to present feedback.

Execution: Some mechanism is needed to provide feedback based on the parameters identified. For example,

IF *GOAL = present response [4.2.2]*
THEN *present response within parameters specified by CIINFO, CA, PE, PR, PD, and SR.*

Next step: Reset variables for the next circuit through the model (Subgoal 4.2.3).

Subgoal 4.2.3: Reset variables for next goal

Function: This goal is fired to reset the variables for the next cycle through the model. Variables are reset for three conditions--to present more information on the same topic, to elicit more performance on the same topic, or to present more information on a new topic.

Reasons for Goal Selection:

1) If feedback has been presented.
   Example rule:

   IF *GOAL = present response [4.2.2]*
   response has been presented
   THEN *GOAL = reset variables for next goal [4.2.3]*

Outcome: A decision to reset variables for the next circuit through the model.

Next step: Reset variables to either return to Goal 1 within the same topic (Subgoal 4.2.3.1), return to Goal 2 within the same topic (4.2.3.2), or return to Goal 1 with a change in topics (4.2.3.3).

Subgoal 4.2.3.1: Reset variables to return to Goal 1

Function: This goal is fired to reset variables for another circuit through the model within the same topic - either for clarification or to present another aspect of the topic.

Reasons for Goal Selection:

1) If topic presentation is not yet complete, but the student is making satisfactory progress.
   Example rule:

   IF *GOAL = reset variables for next goal [4.2.3]*
   TOPICPROGRESS = early OR midway OR nearly complete
   LOCPERF > criterion
   THEN *GOAL = reset variables to return to Goal 1 [4.2.3.1]*

Outcome: A decision to reset variables to return to Goal 1 within the same topic.

Execution: A rule is needed to reset the variables; For example,

IF *GOAL = reset variables to return to Goal 1 [4.2.3.1]*
THEN *reset the following variables to their defaults: (list of variables)*

Next step: Provide situated instruction (Goal 1).

Subgoal 4.2.3.2: Reset variables to return to Goal 2

Function: This goal is fired to elicit performance again on the same topic - either to give the student more practice, or because the student did not perform well previously.

Reasons for Goal Selection:

1) If topic presentation is not complete, and the student needs more practice.
   Example rule:

   IF GOAL = reset variables for next goal [4.2.3]
   TOPICPROGRESS = early OR midway OR nearly complete
   LOCPERF < criterion
   THEN GOAL = reset variables to return to Goal 2 [4.2.3.2]

Outcome: A decision to reset variables to return to Goal 2 within the same topic.

Execution: A rule is needed to reset the variables. For example,

IF GOAL = reset variables to return to Goal 2 [4.2.3.2]
THEN reset the following variables to their defaults: (list of variables)

Next step: Elicit performance (Goal 2).

Subgoal 4.2.3.3: Reset variables to start new topic

Function: This goal is fired to advance to the next topic within the course/curriculum and reset variables for another complete cycle through the model.

Reasons for Goal Selection:

1) If student has mastered the current topic.
   Example rule:

   IF *GOAL = reset variables for next goal [4.2.3]*
   TOPICPROGRESS = complete
   LOCPERF > criterion
   TOPICPERF(topic x) = mastery
   THEN *GOAL = reset variables to start new topic [4.2.3.3-*

Outcome: A decision to reset variables and provide situated instruction on a new topic.

Execution: A rule is needed to reset the variables.

IF *GOAL = reset variables to start new topic [4.2.3.3]*
THEN *reset the following variables to their defaults: (list of variables)*
CURRTOPIC = topic x + 1

Next step: Provide situated instruction (Goal 1).